Extreme Weather Events and Corporate Payout Policy

Evidence from U.S. Public Firms

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Abstract

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Five key words:	corporate payout policy, extreme weather events, weather-shock severity, carbon-intensity, share repurchases

Purpose:

The purpose of this thesis is to examine how extreme weather events affect corporate payout policy among U.S. public firms. The study examines heterogeneity across payout channels, weather-shock severity, carbon intensity, and climate policy uncertainty.

Methodology:

This thesis employs a panel-data approach using two-way fixed-effects models on an unbalanced panel of U.S. S&P 1500 firms from 2008-2025. Extreme weather events are measured using NOAA weather-event data matched to firms' headquarters states. The empirical analysis distinguishes between overall weather exposure and economically severe events using alternative severity thresholds.

Theoretical perspectives:

The thesis draws primarily on corporate finance theories related to precautionary behavior, financial flexibility, payout policy, climate-related financial risk, and climate policy uncertainty. In addition, the thesis incorporates insights from climate-science literature to support the selection and classification of climate-linked extreme weather events.

Empirical foundation:

Firm-level financial data are obtained primarily from S&P Capital IQ and Bloomberg, while weather variables are constructed using the NOAA Storm Events Database matched to firms' headquarters states. The thesis additionally employs Gavriilidis' (2021) CPU index.

Conclusions:

The findings report positive payout responses following financially material extreme weather shocks rather than the uniform payout reductions predicted by precautionary-liquidity arguments and prior climate-payout literature. These effects are concentrated primarily in the repurchase channel, while dividends remain stable. Non-carbon-intensive firms respond substantially more positively than carbon-intensive firms. CPU does not meaningfully moderate firms' responses to extreme weather events.

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Abbreviations

CPU	Climate Policy Uncertainty
EPU	Economic Policy Uncertainty
ESG	Environmental, Social and Governance
GDP	Gross Domestic Product
GHG	Greenhouse Gas Emissions
IPCC	Intergovernmental Panel on Climate Change
NOAA	National Oceanic and Atmospheric Administration
NGFS	Network for Greening the Financial System
OLS	Ordinary Least Squares
ROA	Return on Assets
R&D	Research and Development
SIC	Standard Industrial Classification
TCFD	Task Force on Climate-related Financial Disclosures
TWFE	Two-way Fixed Effects

1. Introduction

1.1 Background

Climate-related physical risks have become a central concern for firms, investors, and policymakers. The World Economic Forum's *Global Risks Report 2026* identifies extreme weather events as the most severe global risk over the next decade, with environmental risks accounting for half of the top ten long-term risks (WEF, 2026). This is consistent with recent climate trends. According to the National Oceanic and Atmospheric Administration (NOAA), 2024, 2023, and 2025 were the three warmest years since the beginning of global records (NOAA, 2026). In the United States alone, NOAA estimates that weather-related disasters caused approximately $183 billion in losses in 2024, while extreme weather events are increasingly disrupting infrastructure, supply chains, labor productivity, and regional economic activity (NOAA, 2025; USGCRP, 2023). As a result, extreme weather has become a material source of firm-level financial risk, with prior research linking severe weather exposure to higher financing costs, weakened operating conditions, heightened default risk, and worsening investor sentiment (Huang et al., 2025; Cerón et al., 2024; Dessaint and Matray, 2017).

1.2 Problem Discussion

A growing literature documents that extreme weather events affect corporate financial policy through multiple channels. Studies on hurricanes, extreme rainfall, and broader climate exposure show that firms respond to weather shocks by increasing cash holdings, relying more heavily on external financing, and adopting more conservative financial policies (Brown et al., 2021; Chen et al., 2023; Dessaint and Matray, 2017). Severe weather events can additionally disrupt firms' financing conditions by impairing bond-market access, increasing reliance on bank borrowing, and shortening debt maturities, particularly for uninsured and financially constrained firms (Collier et al., 2025; Ivanov et al., 2022; Massa and Zhang, 2021).

Overall, this literature suggests that extreme weather events affect firms not only through physical disruption, but also through tighter liquidity conditions and a weaker financing environment. Since payout decisions represent a trade-off between distributing cash to shareholders and retaining internal funds for precautionary motives, liquidity preservation, and investment needs (Chay and Suh, 2009), extreme weather shocks may directly affect firms' payout policies. Existing studies on hurricanes, extreme rainfall, and abnormal temperatures generally predict a negative relationship between extreme weather exposure and corporate payouts, as firms are expected to preserve liquidity rather than distribute it following severe shocks (Attig et al., 2021; Dessaint and Matray, 2017; Massa and Zhang, 2021; Trinh, 2025). However, other research suggests that insurance payouts, public aid, disaster loans, and reconstruction-related demand can partially offset localized disruptions and support corporate recovery (Fan, 2025; Gallaher et al., 2023; Liu et al., 2025). Consequently, the payout effects of realized weather shocks may differ systematically across firms and events rather than being uniformly negative.

An additional unresolved question concerns which payout channel primarily carries the adjustment following extreme weather events. Dividends are widely documented as sticky, as managers are reluctant to cut them given the negative signal associated with dividend reductions, whereas share repurchases are more discretionary and can be adjusted more flexibly (Brav et al., 2005; Jagannathan et al., 2000; Lintner, 1956). While recent climate-payout studies provide evidence that climate risk affects shareholder distributions, evidence remains limited on whether realized extreme weather shocks affect dividends and repurchases differently. This distinction is important because total payout effects may mask opposing or channel-specific responses.

1.3 Purpose and Research Question

The purpose of this thesis is to examine how localized extreme weather shocks affect the corporate payout policy of U.S. public firms. The analysis combines firm-year payout data for S&P 1500 firms with localized extreme weather-event data from NOAA's Storm Events Database and matches weather events to firms by headquarters state. The analysis focuses on total payouts as well as the two primary payout channels, dividends and share repurchases, and further examines heterogeneity across weather-shock severity, carbon intensity, and climate policy uncertainty (CPU). The final sample consists of 16,540 firm-year observations from 1,139 unique firms during the 2008-2025 period.

To address the purpose of this study, the following research questions are examined:

RQ1: How do localized extreme weather events affect the payout policy of U.S. public firms?

RQ2: Do payout responses differ across payout channels, weather-shock severity, and firm-level climate vulnerability?

1.4 Main Findings

Our findings show that localized extreme weather events do not lead to the uniform payout reductions predicted by precautionary-liquidity arguments and documented in prior climate-payout literature. In contrast to studies such as Dessaint and Matray (2017) and Chen et al. (2023), we find no robust evidence that severe realized weather shocks reduce total payouts or dividend distributions. Instead, we find significantly positive payout responses driven almost entirely by increases in share repurchases, with these effects emerging for financially material weather events exceeding the $100 million damage threshold. These findings suggest that severe realized weather shocks do not uniformly translate into financial distress for large publicly listed firms and that insurance coverage, recovery liquidity, external financing capacity, and operational diversification may partially offset localized disruptions. By contrast, dividend payouts remain comparatively stable across specifications, consistent with the sticky nature of dividends. Further, payout responses differ systematically across firms, with carbon-intensive firms responding substantially less positively to severe weather shocks than non-carbon-intensive firms. Additional analyses further show that these effects operate primarily through changes in payout size rather than firms' binary payout decision. Finally, we find no evidence that climate policy uncertainty moderates firms' payout responses to realized extreme weather events.

1.5 Contribution

This thesis contributes to the literature in four main ways. First, we examine a broader set of selected NOAA-based realized extreme weather events in a U.S. public-firm setting and link them directly to corporate payout policy. In doing so, we extend prior studies that focus on narrower shock types such as hurricanes or abnormal temperatures by examining realized physical events rather than broad climate-risk proxies. Second, we examine payout composition by separating total payouts into dividends and share repurchases, thereby accounting for differences in payout flexibility across payout channels. Third, we show that payout responses to realized extreme weather shocks differ systematically between carbon-intensive and non-carbon-intensive firms, extending the growing climate-finance literature to firm heterogeneity in the context of corporate payout policy. Fourth, we extend the analysis by examining whether climate policy uncertainty (CPU) moderates firms' payout responses to realized extreme weather shocks.

1.6 Limitations

This study is not without limitations. First, matching extreme weather events to firms by headquarters state remains an imperfect proxy for a firm's actual operational exposure, particularly for geographically diversified firms. Second, since repurchases can be adjusted more flexibly and at higher frequencies than dividends, the annual research design may not fully capture short-term payout adjustments following extreme weather events.

The remainder of this paper is structured as follows: Section 2 provides the relevant theoretical background, while Section 3 reviews the relevant literature. Section 4 develops the hypotheses. Section 5 describes the data, sample construction, and variable construction. Section 6 outlines the empirical framework, and Section 7 presents and discusses the empirical results. Section 8 concludes the paper.

2. Theoretical Background

2.1 Climate Change and Increasing Risk of Extreme Weather Events

Climate change has evolved from a primarily environmental concern into a systemic economic and financial risk. The *World Economic Forum Global Risks Report 2026* identifies extreme weather events as the most severe global risk over the next decade (WEF, 2026). This growing relevance is also reflected in catastrophe-loss data. Munich Re (2026a) reports that natural disasters caused approximately $224 billion in global losses in 2025, while weather-related disasters accounted for approximately 92% of total catastrophe losses. These developments suggest that climate-related weather events increasingly affect not only environmental systems, but also economic activity, infrastructure, and financial markets.

Scientific evidence suggests that climate change contributes to both the increasing frequency and severity of several types of extreme weather events. According to the Intergovernmental Panel on Climate Change (IPCC, 2021a), human-induced greenhouse gas emissions have unequivocally warmed the atmosphere, oceans, and land, thereby increasing the likelihood of certain extreme weather events. The IPCC reports specifically strong evidence for more frequent and severe heatwaves, increases in heavy precipitation events, more severe drought conditions in some regions, intensified wildfire-conducive conditions, and a higher proportion of intense tropical cyclones.

In this thesis, the terms “extreme weather events”, “severe weather events”, and “weather shocks” are used interchangeably to describe unusually severe and disruptive weather-related events with the potential to generate substantial physical, operational, and economic damages to firms and local economies. This terminology broadly follows the NOAA Storm Events framework.

Many climate-sensitive hazards closely overlap with what the insurance industry classifies as secondary perils such as floods, severe thunderstorms, and wildfires, whereas peak perils refer to events like hurricanes and earthquakes. This suggests that several of the weather events most strongly linked to climate change are also becoming increasingly economically costly. In 2025, secondary perils accounted for approximately 92% of global insured natural-catastrophe losses (Aon, 2026; Munich Re, 2026b; Swiss Re, 2026). The Fifth National Climate Assessment concludes that climate-related hazards increasingly disrupt U.S. economic activity through damages to infrastructure, transportation systems, labor productivity, supply chains, and regional economic activity (USGCRP, 2023).

As climate-linked extreme weather events become more frequent and severe, their economic and financial implications also become more relevant for firms and financial markets. The consequences of such events extend beyond direct physical destruction, as climate-related physical risks generate cascading disruptions across infrastructure systems, transportation networks, supply chains, labor markets, energy systems, and insurance markets (IPCC, 2022b; USGCRP, 2023; WEF, 2026). Firms may therefore be affected not only through direct damages, but also through indirect channels such as operational interruptions, higher operating costs, reduced labor productivity, changing regional demand conditions, and broader business interruption losses (Collier et al., 2025; TCFD, 2017). Consequently, climate-linked extreme weather events can be understood as financially material disturbances with potential implications for firms' operational resilience, liquidity management, financing conditions, and corporate financial policy decisions.

The U.S. represents a particularly relevant setting for studying climate-linked extreme weather risk because of its broad exposure to multiple categories of extreme weather events and the substantial economic losses associated with them. According to NOAA (2025), weather- and climate-related disasters caused approximately $183 billion in damages in the U.S. during 2024, while Munich Re (2026b) describes the U.S. as the global loss epicenter of weather-related disasters, accounting for 81% of total insured losses in 2025. Climate-related hazards within the U.S. are geographically heterogeneous, with regions exposed to different combinations of hurricanes, flooding, droughts, heatwaves, wildfires, and heavy precipitation events (USGCRP, 2023). This heterogeneity creates substantial regional variation in realized local weather exposure across firms and industries.

2.2 Physical Risk versus Transition Risk

The climate-finance literature commonly distinguishes between physical risks and transition risks as the two primary channels through which climate change may affect firms, financial markets, and the broader economy (TCFD, 2017; NGFS, 2019). Physical risks arise from climate-related weather events and long-term environmental changes, whereas transition risks emerge from the economic adjustment toward a lower-carbon economy. These two dimensions affect firms through different transmission channels and time horizons.

According to the Task Force on Climate-related Financial Disclosures (TCFD, 2017), physical risks can further be divided into acute and chronic risks. Acute physical risks refer to event-driven climate hazards such as hurricanes, floods, droughts, wildfires, heatwaves, and severe storms, which may disrupt firms through direct damages and indirect effects on supply chains, labor productivity, infrastructure, operating conditions, and regional demand. Chronic physical risks, on the other hand, refer to gradual environmental changes such as rising average temperatures, sea-level rise, and changing precipitation patterns. Although chronic risks emerge more gradually, they may still materially affect firms through changing operating environments, infrastructure requirements, insurance availability, and long-term adaptation costs. Importantly, chronic climate risks such as rising temperatures and changing precipitation patterns may also contribute to the increasing frequency and severity of certain acute hazards (TCFD, 2017; NGFS, 2019; IPCC, 2022b; USGCRP, 2023).

Transition risks, in contrast, arise from policy, technological, economic, and societal adjustments associated with the transition toward a lower-carbon economy. The TCFD (2017) and the Network for Greening the Financial System (NGFS, 2019) emphasize that transition-related pressures may emerge through climate regulation, carbon pricing, technological change, shifts in consumer preferences, reputational concerns, and evolving investor expectations. Such developments may affect firms' production costs, financing conditions, competitive positions, and asset valuations. Transition risks are particularly relevant for carbon-intensive firms whose business models rely more heavily on emissions-intensive production processes, fossil fuels, or carbon-intensive supply chains. These firms may therefore face greater regulatory exposure, higher transition costs, and stronger investor scrutiny.

Physical and transition-related climate exposures are often interconnected. Bolton et al. (2020) argue that climate-related financial risks are characterized by substantial uncertainty, non-linearity, and potentially cascading economic effects. Additionally, Giglio et al. (2021) emphasize that climate-related exposures differ significantly across firms, industries and geographic regions, implying heterogeneous financial consequences of climate risk. Consequently, some firms may simultaneously face both heightened physical and transition-related exposure. This is particularly relevant for carbon-intensive firms, which may not only experience physical disruptions from extreme weather events, but may also face greater financing frictions, investor concerns and climate policy uncertainty (CPU). The interaction between physical and transition-related climate risks may therefore have an important implication for firms' operational resilience, financing conditions, liquidity management, and broader corporate financial policies. This transmission mechanism may be particularly important for corporate payout decisions, as firms may adjust their payouts in response to both realized climate shocks and transition uncertainty.

2.3 Insurance, Disaster Aid, and Recovery Liquidity

The financial consequences of extreme weather events depend not only on the severity of the shock itself, but also on the extent to which firms are able to transfer, absorb, or smooth weather-related losses. While extreme weather events may generate substantial physical damages and operational disruptions, the resulting net financial impact on firms can vary considerably depending on insurance coverage, access to external financing, and firms' overall financial resilience (Endendijk et al., 2024; Swiss Re, 2026). Consequently, realized weather shocks do not necessarily translate one-to-one into immediate financial distress.

Insurance represents one important mechanism through which firms may partially transfer climate-related risks. Property insurance can compensate for damaged physical assets, while business interruption insurance may help offset temporary revenue losses arising from operational disruptions or supply-chain interruptions. This is important because the economic consequences of extreme weather often extend beyond direct asset destruction and may include substantial indirect losses associated with interrupted business activity (Collier, 2025; Endendijk et al., 2024). At the same time, insurance coverage is often incomplete due to deductibles, delayed claims processing, rising premiums, coverage exclusions, and underinsurance. This is particularly relevant for climate-sensitive secondary perils such as floods, wildfires, and severe convective storms, where protection gaps remain substantial despite increasing economic losses (Swiss Re, 2026).

In addition to private insurance, severe weather events are often followed by reconstruction spending, emergency lending, and disaster assistance measures such as support provided by the Federal Emergency Management Agency (FEMA) or Small Business Administration (SBA) disaster loans, which may help stabilize local economic activity and recovery in affected regions. Although these mechanisms are often targeted toward households, small businesses, and public infrastructure rather than large publicly listed firms directly, they may still indirectly affect larger firms by stabilizing local demand, restoring infrastructure, and supporting suppliers, and customers in affected regions (Gallagher et al., 2023; Collier et al., 2024). These recovery channels can therefore reduce the broader local liquidity and demand pressures associated with severe physical shocks, even if the direct relevance for large firms depends on their operational footprint, local exposure, and access to private financing.

Importantly, the economic and financial consequences of extreme weather events are unlikely to increase linearly with the mere number of realized weather events. While many smaller weather events may generate only limited operational disruptions, sufficiently severe disasters may trigger substantial physical damages, financing frictions, insurance gaps and other economic spillovers (Collier et al., 2025; Swiss Re, 2026). Consequently, the financial relevance of realized weather shocks likely depends not only on weather exposure itself, but also on the economic materiality of the underlying events.

This distinction is particularly important in the context of payout policy, as severe disasters may increase liquidity needs, precautionary motives, and financing constraints relative to more routine weather. The broader catastrophe-risk literature emphasizes that large disaster events are characterized by nonlinear and fat-tailed economic losses, implying that financially material disasters may generate disproportionately large corporate and financial-market effects (Froot, 2001; Pindyck and Wang, 2013).

2.4 Payout Policy: Dividends versus Repurchases

Firms typically distribute cash to shareholders through dividends or share repurchases. The payout literature emphasizes important differences in the degree of commitment, flexibility and the informational implications associated with these distribution channels. The dividend literature characterizes dividends as relatively persistent and smooth over time. Lintner (1956) shows that managers are reluctant to reduce dividends once established and instead adjust payouts only gradually in response to changes in long-term earnings expectations. Consistent with this view, prior research documents a significantly negative stock market reaction following dividend cuts (Denis et al., 1994; Ghosh and Woolridge, 1988). More recent studies further report that dividend smoothing is especially pronounced among publicly listed firms facing stronger investor scrutiny and capital-market pressures (Michaely and Roberts, 2012). Similarly, Brav et al. (2005) find that managers perceive dividend reductions as costly because investors often associate them with a weakening earnings outlook or financial distress. Consequently, dividends are commonly viewed as sticky and represent the less flexible component of corporate payout policy.

In contrast, share repurchases are traditionally viewed as a more discretionary payout mechanism. Repurchase programs do not require firms to maintain fixed future distributions and therefore allow managers greater flexibility in both timing and magnitude of payouts in response to changing financial conditions (Stephens and Weisbach, 1998). Jagannathan et al. (2000) further argue that repurchases are used by firms with temporary cash flows, while dividends are linked to more permanent cash flows. As a result, repurchases may enable firms to distribute excess cash while preserving financial flexibility under volatile earnings conditions.

Over recent decades, repurchases have become increasingly important within U.S. corporate payout policy. Fama and French (2001) document a substantial decline in the proportion of U.S. firms paying cash dividends, while subsequent research suggests that repurchases increasingly substitute for traditional dividend distributions. Grullon and Michaely (2002) and Skinner (2008) show that repurchases evolved from a secondary payout mechanism into a dominant form of shareholder distribution among U.S. firms. At the same time, firms with established dividend histories often continued to maintain regular dividend payments while increasingly relying on repurchases to absorb volatility in earnings and internally generated cash flows. However, the literature also emphasizes that repurchases may serve additional purposes beyond shareholder payouts, such as signaling undervaluation, funding acquisitions, offsetting dilution from employee stock options, or managing reported EPS (Allen and Michaely, 2003; Brav et al., 2005; Skinner, 2008). Overall literature suggests dividends are the sticky component of payout, whereas repurchases provide greater distribution flexibility under changing market conditions

2.5 Precautionary Motives, Signaling and Financial Flexibility

Payout policy reflects the trade-off between distributing cash to shareholders and retaining internal funds for liquidity, investment, and risk management. This trade-off is closely linked to the precautionary motive for corporate cash holdings, which argues that firms preserve internal funds to protect themselves against future financing shortfalls and costly external financing (Opler et al., 1999). Prior payout literature suggests that mature and profitable firms with high levels of retained earnings are more likely to distribute cash to shareholders, consistent with lifecycle theories of payout policy (DeAngelo et al., 2006). Corporate-finance literature further emphasizes that internal liquidity becomes especially valuable when firms face financing frictions, uncertain future cash flows, or significant future investment needs (Froot et al., 1993; Kim et al., 1998). In these settings, the value of financial flexibility increases because cash reserves allow firms to reduce dependence on costly or uncertain external financing (Lie, 2005; Rapp et al., 2014). Firms with insufficient liquidity may otherwise be forced to cut investment, reduce dividends, or raise external financing under unfavorable conditions (Opler et al., 1999).

Consistent with this theory, Bates et al. (2009) show that the long-run increase in U.S. corporate cash holdings is largely explained by higher cash-flow risk, greater R&D intensity, and fewer working-capital substitutes, which they interpret as evidence of the precautionary motive. Begenau and Palazzo (2021) further link this trend to stronger precautionary savings among R&D intensive firms with high growth potential and uncertain future financing needs. Acharya et al. (2012) additionally emphasize that higher precautionary cash holdings do not necessarily imply lower underlying risk, as firms exposed to greater expected liquidity risk may already have accumulated larger cash reserves in accordance with the precautionary motive. Extending these precautionary motive arguments to payout policy, Chay and Suh (2009) investigate how cash-flow uncertainty affects shareholder distributions and find that firms with higher uncertainty tend to reduce shareholder payouts in order to retain financial flexibility. The authors argue that managers may avoid committing to high and inflexible payouts when future cash flows are difficult to sustain, particularly given the stickiness of dividends and the negative market reaction associated with dividend cut.

Extreme weather events fit into this framework because, as discussed in earlier sections, they may generate liquidity shortfalls and uncertainty regarding future cash flows and financing conditions. Severe weather shocks can therefore increase the value of internal cash holdings relative to shareholder distributions. Even when physical damages are temporary, firms may respond by conserving internal resources to protect investment capacity and reduce dependence on external financing. Dessaint and Matray (2017) show that hurricane salience increases managers' perceived liquidity risk and leads firms to increase cash holdings, which is consistent with precautionary liquidity preservation.

Although the precautionary motive provides the dominant theoretical prediction, payout responses to severe weather shocks may not necessarily be uniformly negative across firms. Shareholder distribution may additionally reflect signaling considerations and firms' broader recovery capacity. Jensen's (1986) free-cash-flow argument suggests that distributing cash can reduce managerial discretion and mitigate agency problems. Further, repurchases may communicate undervaluation, managerial confidence, or balance-sheet strength (Allen and Michaely, 2003; Skinner, 2008). Finally, insurance coverage and post-disaster recovery may additionally mitigate the financial pressure associated with severe weather shocks. Overall, while precautionary motives suggest lower shareholder payouts following severe weather shocks, the overall payout response may vary depending on recovery capacity and signaling incentives.

3. Literature Review

3.1 Extreme Weather and Corporate Financial Policy

A growing climate-finance literature suggests that realized extreme weather events can materially affect firms through operational disruptions, financing frictions, liquidity pressures, and corporate financial policy. Severe weather events can disrupt firms through direct damages to assets as well as indirect disruptions to infrastructure, transportation networks, supply chains, labor productivity, and regional demand conditions (TCFD, 2017; USGCRP, 2023). Because firms operate within interconnected production and financial networks, weather shocks may additionally propagate across suppliers, customers, and regional economies (Collier et al., 2025). Barrot and Sauvagnat (2016), for instance, show that natural disasters affecting suppliers reduce sales growth among downstream customer firms, highlighting that firms may be economically affected even without direct physical exposure.

Several studies document that extreme weather shocks increase firms' precautionary demand for liquidity by weakening cash flows, increasing uncertainty, and raising external financing needs. Firms exposed to severe weather disruptions respond by increasing cash holdings, relying more heavily on external financing, and preserving financial flexibility (Brown et al., 2021; Dessaint and Matray, 2017; Chen et al., 2023). These findings suggest that weather shocks increase firms' demand for precautionary liquidity and strengthen incentives to preserve financial flexibility under heightened uncertainty.

The literature further suggests that extreme weather events may tighten financing conditions and impair firms' access to capital markets. Disaster-related lending reallocations can reduce credit availability for indirectly exposed firms and induce more conservative lending behavior among financial institutions (Ivanov et al., 2022; Rehbein and Ongena, 2025; Schüwer et al., 2019). Severe weather shocks may additionally alter firms' debt structure and financing choices by impairing access to specific financing channels. Massa and Zhang (2021), for example, study Hurricane Katrina and show that disruptions in insurance markets and forced asset sales by insurance companies impaired access to bond financing, leading firms to substitute toward bank borrowing and shorter debt maturities. Further, climate-related risks are increasingly associated with higher financing costs, tighter borrowing conditions, and more conservative financial policies (Allman, 2020; Cerón et al., 2024).

Beyond liquidity and financing effects, the literature further suggests that severe weather shocks can materially affect firms' operations, profitability, and valuation. Extreme weather events may reduce labor productivity, increase operating costs, disrupt production processes, and weaken firm value, particularly when firms face concentrated local exposure or limited recovery capacity (Acharya et al., 2023; Collier et al., 2025; Liu et al., 2025). At the same time, firms may actively adapt to climate-related risks through geographic diversification and operational reallocation. Acharya et al. (2023), for instance, find that firms respond to heat shocks by reallocating across establishments and regions, while Bai et al. (2024) document that firms exposed to sea-level rise diversify geographically through acquisitions in less vulnerable regions. Liu et al. (2025) further show that geographically diversified firms appear more resilient to local weather shocks because climate disruptions affect a smaller share of their total operations.

Overall, the above literature suggests that extreme weather events affect firms through operational, liquidity, and financing channels. These financial pressures are highly relevant for corporate payout policy as payout decisions reflect the trade-off between retaining internal funds and distributing cash to shareholders.

3.2 Extreme Weather and Corporate Payout Policy

3.2.1 Precautionary Motives and Liquidity Preservation

Severe weather shocks may reduce shareholder distributions by increasing firms' incentives to preserve internal liquidity and financial flexibility. As discussed in Sections 2.5 and 3.1, severe weather-related disruptions can weaken cash flows, increase financing needs, and raise uncertainty regarding future operating conditions, which may lead firms to retain internal funds rather than distributing cash to shareholders.

Several studies document that firms respond to extreme weather exposure by adopting conservative financial policies aimed at strengthening financial resilience. Chen et al. (2023), for instance, show that firms exposed to extreme rainfall increase cash holdings, rely more heavily on long-term debt, reduce short-term debt exposure, and lower cash dividend payouts in response to heightened uncertainty and liquidity risk. Further, Huang et al. (2018) find that firms exposed to higher climate risk hold more cash, rely less on short-term debt, and distribute lower cash dividends, which the authors interpret as evidence that firms adjust financial policies to hedge against greater operating cash-flow volatility and liquidity risk. Additional evidence suggests that extreme weather events increase financing costs, worsen operating conditions, and heighten default risk, which reinforces firms' incentives to preserve precautionary liquidity and financial flexibility (Huang et al., 2025).

Beyond direct financing effects, extreme weather additionally affects managerial risk perceptions, which may amplify precautionary financial behavior. Dessaint and Matray (2017) show that firms located near hurricane strikes increase corporate cash holdings even when their actual physical exposure remains unchanged. The authors argue that salient disaster events temporarily increase managers' perceived liquidity risk. Overall, this literature suggests that severe weather shocks reduce shareholder payouts because firms seek to preserve internal liquidity and strengthen financial resilience.

3.2.2 Payout Flexibility under Climate Risk

As discussed in Section 2.4, dividends and repurchases differ substantially in terms of flexibility, persistence, and signaling implications. This is particularly important under climate-related uncertainty and severe weather shocks because repurchases allow for more discretion regarding payout timing and magnitude. Firms seeking to preserve liquidity and financial flexibility may therefore adjust shareholder distributions through repurchases rather than dividends.

Empirical evidence supports this payout-substitution mechanism. Trinh (2025) finds that greater long-term climate exposure is associated with lower dividend payouts, particularly among climate-vulnerable firms. While Chang et al. (2024) focus on broader climate risk rather than realized extreme events, the authors show that higher climate risk is associated with lower total payouts and dividends, but higher repurchases. Their findings suggest that firms increasingly substitute toward the more flexible repurchase channel when climate-related uncertainty raises the value of financial flexibility.

3.2.3 Insurance, Disaster Aid and Recovery Liquidity

Another strand of literature emphasizes that the net financial consequences of realized weather shocks depend partly on insurance coverage, disaster assistance, and post-disaster recovery liquidity. As discussed in Section 2.3, insurance and recovery mechanisms may partially offset the liquidity pressures generated by severe physical shocks.

Fan (2025) finds that flood insurance materially improves post-disaster business recovery, leading to stronger employment and sales outcomes following severe flooding events. Gallagher et al. (2023) similarly show that federal disaster assistance mitigates financial distress and improves business survival and employment in tornado-affected regions. Liu et al. (2025)

further document that state-level financial assistance partially offsets the negative valuation effects associated with severe weather shocks.

However, the literature also emphasizes that insurance coverage and disaster aid are often incomplete. Collier et al. (2025) show that many firms affected by Hurricane Harvey lacked sufficient insurance coverage, were denied formal financing, or relied on informal funding sources following the disaster. The broader catastrophe-risk literature similarly argues that severe climate-related disasters are difficult to insure completely because catastrophic events generate highly correlated and fat-tailed losses (Froot, 2001; Kousky and Cooke, 2012).

Consequently, the financial and corporate payout effects of extreme weather shocks may differ substantially depending on firms' access to insurance coverage, recovery liquidity, and external financing conditions.

3.3 Severity and Economic Materiality of Weather Shocks

Building on the discussion of shock severity in Section 2.3, an important strand of literature argues that not all weather events are equally relevant from a financial perspective. While broad weather-exposure measures capture overall climate activity, economically material disasters are substantially more likely to generate operational disruptions, financing frictions, liquidity pressures, and broader regional spillovers.

The catastrophe-risk literature characterizes severe disasters as low-probability but extremely costly events associated with fat-tailed risk distributions and substantial aggregate losses (Froot, 2001; Pindyck and Wang, 2013). Severe disasters can generate disproportionate indirect effects through infrastructure disruptions, insurance gaps, financing constraints, and regional economic spillovers (Kousky and Cooke, 2012; Collier et al., 2025). Gourio (2013) further shows that higher disaster risk increases credit spreads and risk premia, reduces investment, and induces firms to deleverage, suggesting that severe shocks may materially affect firms' financing conditions and corporate financial policy.

These considerations are particularly relevant for empirical climate-finance research because broad event-count measures may assign identical weights to economically minor and catastrophic events. Several studies therefore focus on economically material weather disruptions when analyzing corporate financial outcomes, as routine weather events generate more limited financial consequences relative to severe disasters. For example, Collier et al. (2025) show that the strongest financial-distress effects emerge in the most severely flooded regions during Hurricane Harvey. Similarly, Brown et al. (2021), Chen et al. (2023), and Liu et al. (2025) focus on disruptive weather events with economically material corporate consequences rather than on routine weather variation.

The broader catastrophe and insurance literature further suggests that severe disasters may impair firms' access to external financing and overwhelm existing insurance and recovery mechanisms once damages exceed economically material levels. As a result, the financial consequences of severe weather shocks may increase disproportionately with disaster severity rather than linearly with the number of realized events. Consequently, damage-based thresholds may provide a more economically meaningful measure of realized climate-related shocks than broad event-frequency measures alone.

3.4 Carbon Intensity and Heterogeneous Climate Vulnerability

As discussed in Section 2.2, firms differ substantially in their exposure to physical and transition climate risks. The climate literature emphasizes that climate-related risks are highly heterogeneous across firms and industries, which implies that firms respond differently to weather shocks depending on their broader climate vulnerability.

Prior literature shows that carbon-intensive firms are particularly exposed to climate-related financial pressures because they face stronger transition risk and often operate capital-intensive business models with long-lived assets. At the same time, related evidence on physical climate risk shows that firms exposed to heat stress or sea-level risks face higher financing costs and may need to adjust their operations or geographic footprint in response to extreme weather exposure (Acharya et al., 2023; Allman, 2020; Bai et al., 2024). Nguyen and Phan (2020) show that higher carbon risk leads heavy-emitting firms to reduce leverage, particularly when financial constraints are more pronounced, consistent with the view that climate-related risks increase financial distress and strengthen incentives to preserve financial flexibility. Further studies report that carbon-intensive firms face higher financing costs, greater regulatory uncertainty, and weaker investor demand under increasing climate-policy pressure (Bolton and Kacperczyk, 2021; Cerón et al., 2024; Hoang, 2022). Trinh (2025) finds that long-term climate exposure is associated with lower dividend payouts, particularly among firms that are more exposed to climate transition risk. Overall, this suggests that climate-vulnerable firms may respond more conservatively to extreme weather shocks by placing greater focus on precautionary liquidity and financial flexibility than less exposed firms.

3.5 Climate Policy Uncertainty

In addition to realized physical disruptions and their wider financing and liquidity effects discussed in Section 2.3, firms may also face uncertainty regarding the timing, direction, and intensity of future climate regulation. Gavriilidis (2021) conceptualizes CPU as a distinct form of policy uncertainty related to government climate action. Prior research shows that higher CPU reduces investment and R&D activity, especially among carbon-intensive firms (Gavriilidis et al., 2026; Hoang, 2022). Other studies suggest that CPU affects financial markets by shifting investor demand toward green and clean-energy assets (Bouri et al., 2022; Tedeschi et al., 2024).

Similar to extreme weather events, as discussed in previous Sections, the effect of CPU on payout policy is theoretically ambiguous. Precautionary motives imply that firms may preserve internal liquidity under heightened CPU, whereas agency-based arguments suggest that investors demand higher payouts when uncertainty increases managerial discretion over internal funds. Consistent with the latter, Attig et al. (2021) show that economic policy uncertainty (EPU) is positively associated with payouts, while Ayed et al. (2024) document a positive association between CPU and dividend payouts. Preliminary evidence from a prior study on effect of CPU on U.S. corporate payout policy conducted by the authors of this thesis implies that payout responses to CPU may differ across channels and firm types, with adjustment effects appearing more pronounced for repurchases than dividends among carbon-intensive firms.[1]

4. Hypothesis Development

The preceding theoretical background and literature review suggest that extreme weather events may affect corporate payout policy through several interconnected channels. As discussed in the previous sections, extreme weather events may increase firms' liquidity needs, tighten financing conditions, and raise uncertainty regarding future operating and investment needs (Ivanov et al., 2022; Massa and Zhang, 2021; Rehbein and Ongena, 2025). Because payout policy reflects the trade-off between distributing cash to shareholders and retaining internal funds, such disruptions may alter firms' payout decisions. Prior literature suggests that firms exposed to climate-related risks respond by increasing precautionary cash buffers, relying

[1] The study "Climate Policy Uncertainty and Corporate Payout Decisions" (Gokami and Wilbrand, 2026) is an unpublished working paper which can be made available upon request.

more heavily on external financing and adjusting financial policies under heightened uncertainty (Dessaint and Matray, 2017; Chen et al., 2023; Collier et al., 2025).

At the same time, the direction of payout responses remains theoretically ambiguous. While precautionary motives imply lower payouts, signaling incentives, agency considerations, and shock-absorption mechanisms such as insurance coverage and recovery liquidity may partially offset these effects (Brav et al., 2005; Fan, 2025; Gallagher et al.; 2023, Liu et al., 2025). Consequently, we expect extreme weather events to affect firms' payout policy. We therefore formulate our first hypothesis as follows:

H1a: Extreme weather events are associated with adjustments in corporate payout policy.

The literature further argues that the financial consequences of weather shocks depend on their economic severity, because financially material disasters generate disproportionately large operational disruptions, financing frictions, and aggregate losses relative to routine events (Froot, 2001; Gourio, 2013; Kousky and Cooke, 2012). Further evidence shows that the strongest effects of increased financial distress occur in the most severely affected regions, particularly when insurance coverage and external financing access are limited (Collier et al., 2025). Thus, many climate-finance studies focus on economically material weather disruptions rather than broad weather exposure (Brown et al., 2021; Chen et al., 2023; Liu et al., 2025). Hence, we expect that financially material disasters induce stronger payout responses than less severe weather events. We therefore formulate the following sub-hypothesis:

H1b: The payout effects of extreme weather events become stronger as the economic severity of weather shocks increases.

Prior research further suggests that payout responses to extreme weather events differ systematically across payout channels. Dividends are generally characterized as sticky and managers are often reluctant to cut dividends, whereas repurchases provide firms with substantially greater flexibility regarding payout timing and magnitude (Jagannathan et al., 2000; Brav et al., 2005). In addition, repurchases signal managerial confidence and balance-sheet strength (Allen and Michaely, 2003; Skinner, 2008). Consequently, firms seeking to preserve liquidity and financial flexibility following severe weather shocks may adjust shareholder distributions primarily through the more flexible repurchase channel. Consistent with this idea, empirical evidence suggests that firms exposed to climate-related risks and extreme weather events rely more heavily on repurchases relative to dividends when adjusting payout policy under heightened uncertainty (Chang et al., 2024; Trinh, 2025). However, sufficiently severe weather shocks may still affect dividend payouts. Therefore, we formulate our next hypothesis as follows:

H2: Share repurchases respond more strongly to extreme weather events than dividends.

Climate-related risks may not affect all firms equally. Prior literature suggests that carbon-intensive firms are particularly vulnerable because they face greater transition-related pressures, higher financing costs, and stronger investor scrutiny (Bolton and Kacperczyk, 2021; Hoang, 2022; Cerón et al., 2024). In addition, research shows that carbon-intensive firms tend to adopt more conservative financial policies and place greater emphasis on preserving financial flexibility under climate-related risk (Allman, 2020; Huang et al., 2025; Nguyen and Phan, 2020). As a result, carbon-intensive firms may be more likely to adjust shareholder distributions following extreme weather events in order to retain internal liquidity and absorb potential financing pressures. Trinh (2025) further finds that firms with greater climate vulnerability exhibit stronger payout responses to climate-related risks. Consequently, our third hypothesis is as follows:

H3: Carbon-intensive firms exhibit stronger payout response to extreme weather events than non-carbon-intensive firms.

Finally, prior literature suggests that CPU influences firms' financial decisions by increasing uncertainty regarding future regulation, transition costs, and financing conditions (Gavriilidis, 2021; Hoang, 2022). While broader uncertainty-related literature argues that firms reduce payouts under higher cash-flow uncertainty to preserve financial flexibility (Chay and Suh, 2009), empirical evidence on policy uncertainty remains mixed. Attig et al. (2021) find that EPU is positively associated with payouts, whereas Ayed et al. (2021) document a positive association between CPU and dividend payouts, consistent with agency-based arguments. Building on this literature, CPU may influence how firms adjust shareholder distributions following extreme weather shocks by increasing financing uncertainty and strengthening precautionary motives. Hence, our final hypothesis addresses the question whether CPU, as an additional uncertainty channel, moderates firms' payout responses to extreme weather events.

H4: Climate policy uncertainty moderates the relationship between extreme weather events and corporate payout policy.

5. Data and Sample Description

5.1 Sample Construction and Data Sources

Our sample consists of U.S. firms included in the S&P Composite 1500 over the period 2008–2025. The S&P 1500 provides broad coverage across large-, mid-, and small-cap U.S. listed firms and is therefore well suited for analyzing corporate payout policy in a broad U.S. setting. The U.S. setting is particularly suitable for this analysis because firms operate within a common national institutional and regulatory environment while simultaneously facing substantial geographic heterogeneity in localized weather exposure across firms. Consistent with corporate finance research, we exclude financial firms (SIC 6000–6999) because of their limited comparability with non-financial firms in terms of balance sheet structure, regulation, and payout behavior. The resulting dataset is an unbalanced firm-year panel that reflects both changes in the index composition and variation in data availability across firms and years.

Firm-level financial data are obtained from S&P Capital IQ, which provides payout variables, accounting data, and SIC classifications used throughout the analysis. Macroeconomic data on U.S. GDP growth, used as a control variable, are sourced from the World Bank's World Development Indicators database (World Bank, 2026). All firm-level control variables are lagged by one year to mitigate potential simultaneity between firm characteristics and payout decisions.

The broader sample construction begins in 2005 following the implementation of the Kyoto Protocol, which marked an important milestone in the emergence of more systematic climate-policy discussions and increasing regulatory attention toward climate-related risks (Aldy and Stavins, 2007). Starting the sample in the post-Kyoto period is therefore conceptually appropriate given the thesis' focus on climate-related physical and transition risks. In addition, the empirical sample period aligns with the beginning of sufficiently consistent coverage of the CPU index developed by Gavriilidis (2021).

The empirical analysis itself begins in 2008. Although data collection starts in 2005, incomplete early-period coverage for several accounting variables in Capital IQ, particularly retained earnings, substantially reduces the number of usable observations in 2005 to 2007 after applying the sample requirements. The final estimation window from 2008 to 2025 therefore reflects both the conceptual sample design and the need to construct a sufficiently consistent firm-year panel for the empirical analysis. The final estimation sample consists of 16,540 firm-year observations across 1,139 unique firms.

Our analysis is conducted at the annual firm-year level because this frequency is most consistent with the broader payout-policy and climate-risk setting examined in this thesis. While some climate-disaster studies focus on isolated catastrophic events, our setting examines the broader effects of climate-linked extreme weather exposure. Additionally, the financial consequences of extreme weather events often unfold over the fiscal year through operational disruptions, insurance claims, recovery spending, financing adjustments, and liquidity management. Moreover, payout policy, especially dividend policy, is characterized by persistence and relatively infrequent adjustments, while repurchases, despite being more flexible, remain embedded within the broader corporate capital allocation and liquidity planning decisions (Lintner, 1956; Brav et al., 2005). Accordingly, the annual specification is intended to capture the broader net payout response to realized extreme weather exposure over the fiscal year rather than immediate short-term adjustments following individual events.

5.2 NOAA Storm Events Database and Weather Exposure Measures

Data on extreme weather events are obtained from the NOAA Storm Events Database, which records U.S. weather events that are reported to the U.S. National Weather Service. The database includes events that are sufficiently severe to cause loss of life, injuries, significant property damage, and/or disruption to commerce (NOAA, 2026). Because the NOAA database records events separately for each affected county, a single physical event may appear multiple times within the raw dataset. To avoid double counting, we use the distinct NOAA episode ID and retain one observation per unique physical event within each state-year. This approach allows us to construct state-level weather measures based on distinct realized weather episodes rather than county-level event records.

Consistent with the climate-science evidence discussed in Section 2.1, and following related empirical approaches in climate-finance research (e.g., Chen, 2018), we do not retain all event categories reported in the NOAA database. Instead, the analysis focuses on event categories for which climate science suggests relatively stronger and more consistent links to climate change (Table A1). This includes heavy precipitation, floods, droughts, heatwaves, wildfires, storm surge, and intense tropical cyclones (IPCC, 2021a; USGCRP, 2023). In addition, tornadoes, thunderstorms, high winds, and winter storms are also retained in the baseline specification despite comparatively more debated climate-attribution evidence. This reflects both their substantial economic relevance within the U.S. and the broader climate-risk literature emphasizing the growing importance of severe convective storms and other secondary perils in catastrophe-related losses (IPCC, 2021a; Munich Re, 2026b; Swiss Re, 2026;

USGCRP, 2023). Events excluded from the analysis include hail, fog, frost, lightning, and other rare event categories for which climate science provides limited or insufficiently consistent evidence of a climate change signal.

The weather-exposure variable ($\ln Wcount_{st}$) is defined as the logarithm of one plus the total number of distinct NOAA-reported climate-linked weather events occurring within state s during year t. To capture the severity of weather shocks, we additionally construct several threshold-based severity measures using NOAA property-damage estimates. The severity variable ($\ln W_{st}^{(k)}$) is defined as the logarithm of one plus the number of climate-linked weather events in a firm's headquarters state s in year t with property damage exceeding threshold k. We use four severity thresholds ($10 million, $50 million, $100 million, and $500 million) to distinguish between routine weather events and economically material shocks.

All weather measures are constructed using the natural logarithm transformation log(1+N), where N represents the count of qualifying weather events within a given state-year. This transformation addresses positive skewness in the raw data, maps zero-event observations to log(1) = 0, and implies economically plausible diminishing marginal effects of repeated weather exposure; it is applied consistently across all measures and thresholds to ensure comparability.

Finally, all weather variables are standardized into a z-score to improve interpretability and comparability across specifications. Standardization allows the estimated coefficients to be interpreted as the effect of a one-standard-deviation increase in weather exposure or weather-shock severity, rather than the effect of one additional weather event. This is particularly important because the raw NOAA event-count data exhibit substantial variation across states and years. Standardizing the variables also facilitates comparability across alternative measures and severity thresholds used throughout the analysis. Figure 1 illustrates the temporal variation in economically material weather shocks across the sample period.

5.3 Headquarters Data

To link state-year events to the specific firms in our sample, we used the state in which a firm's headquarters was located as a proxy for extreme weather shock exposure. Headquarters-based matching is common in finance-climate and weather-shock research because historical establishment-level exposure data are typically unavailable for large firm samples over extended time periods (e.g., Bai et al., 2024; Brown et al., 2021; Dessaint and Matray, 2017; Trinh, 2025).

As historical headquarters data is not stored in available data providers such as Bloomberg and Capital IQ, we follow the approach of Atanassov et al. (2021) and use the historical headquarter dataset provided by Gao et al. (2021), who extract headquarters data from SEC 10-Q, 10-K and 8-K filings using textual analysis. Related studies similarly use SEC filing-header data, which are often accessed through McDonald's Augmented 10-X Header Data hosted by the Notre Dame Software Repository for Accounting and Finance (e.g., Allman, 2020; Bai et al., 2024; Le et al., 2024).

Because Gao et al.'s dataset covers the period from 2004 to 2022, we extend the headquarters state through 2025 using current headquarters data from Capital IQ as of April 2026. If a firm's headquarters state in April 2026 matched its 2022 headquarter state, we assume that the firm remained headquartered in that state from 2023 through 2025. To test the validity of this assumption we randomly selected 100 firms of this subsample and manually verified their headquarters history. In 100% of these cases, the headquarters state remained unchanged between 2022 to 2025, which provides sufficient support for our approach. For the remaining firms whose April 2026 headquarter state differed from the 2022 location data provided by Gao et al. (28 firms), we conceptually followed Gao et al.'s approach and manually collected 10-K header data and extracted the headquarter state for 2023 to 2025. Our final sample comprises 1455 firms, after excluding S&P Composite 1500 firms that were not headquartered in the U.S.

Although headquarters-based matching is widely used in literature, it remains an imperfect proxy for firms' true operational exposure to local extreme weather events. Large firms may be geographically diversified across establishments, supply chains and revenue streams, which can reduce the impact of local realized weather shocks (Bai et al., 2021). Consistent with this idea, Bai et al. (2021) show that firms can partially diversify this exposure by acquiring firms in less climate-exposed locations. Consequently, headquarter-based measures may overstate the effective exposure of geographically diversified firms and may instead capture broader local economic disruption, managerial salience, or regional climate-risk exposure rather than precise establishment-level damages.

At the same time, Custodio et al. (2025) provide additional support for the use of headquarters-based matching. In their paper on whether climate change affects firm sales, they compare headquarter-based and establishment-level weather exposure measures and report a correlation of 0.86 between the two approaches, which suggests that headquarters-based matching remains a reasonable proxy when establishment-level geographic exposure data are unavailable.

5.4 Carbon Intensity Measures

To classify firms as carbon-intensive, we employ two alternative approaches. Our baseline classification uses a granular 4-digit SIC-code approach to identify carbon-intensive industries. The classification draws on prior climate-finance literature using SIC-based carbon-intensity measures as well as sector-level greenhouse gas (GHG) emissions data published by the U.S. Environmental Protection Agency (2026) (e.g., Basaglia et al., 2022). Since carbon-intensive firms may be more exposed to both physical disruptions and transition-related pressures, the SIC-based classification serves as a proxy for firms' broader climate-related vulnerability rather than a pure transition-risk measure. The corresponding SIC industries and classifications are reported in Table A2.

As an alternative measure, we construct a firm-level emissions variable using Bloomberg Scope 1 and Scope 2 GHG emissions data scaled by firm sales. We follow climate-finance research (e.g., Bolton and Kacperczyk, 2021) and exclude Scope 3 emissions because disclosure remains substantially less consistent and comparable across firms and years. Relative to the SIC-based classification, the emissions-based measure provides a more direct firm-level proxy for carbon intensity and is commonly used in climate-finance research, but is available only for a smaller subset of firms and years. Emissions coverage is concentrated primarily among larger and more transparent firms, which may introduce selection bias related to voluntary ESG disclosure practices across the entire sample period. In our sample, Bloomberg emissions data coverage is largely limited to the period from 2017 to 2024 and covers approximately 32.6% of total firm-year observations over the entire sample period. Consequently, the SIC-based classification serves as a baseline specification, while the emissions-based measure is used as an alternative robustness measure.

5.5 Climate Policy Uncertainty Index

Climate policy uncertainty is measured using the U.S. CPU index developed by Gavriilidis (2021). The index is constructed using textual analysis of major U.S. newspapers and captures the frequency of articles jointly discussing climate-related topics, economic policy, and uncertainty. Following Gavriilidis (2021), we use the narrow version of the index as our baseline measure because it provides a more conservative and precise measure of climate-policy-related uncertainty.

The original CPU index is recorded quarterly. To ensure consistency with our annual firm-level panel, we aggregate the quarterly observations into annual averages. Following

Gavriilidis (2021), the variable is scaled such that a one-unit increase corresponds to a 100-point increase in the index. Figure 2 illustrates the evolution of mean total payouts for carbon-intensive firms and non-carbon-intensive firms alongside the annual CPU index over the sample period.

5.6 Dependent Variables

The main dependent variable is total payouts scaled by total assets ($Payout_{it}$), defined as the sum of cash dividends and share repurchases divided by total assets and expressed as a percentage. Scaling payouts by total assets allows for cleaner interpretation of the results and ensures comparability across firms. Measuring payouts in this way captures the full scope of corporate cash distributions to shareholders, which is particularly important given the increasing importance of share repurchases as a payout mechanism amongst U.S. firms (Brav et al., 2005).

In addition to total payouts, we separately analyze dividends ($Dividends_{it}$) and share repurchases ($Repurchases_{it}$) to examine whether the effects of extreme weather shocks differ across payout channels. This distinction is important because dividends are generally considered more persistent and less flexible, whereas repurchases provide firms with greater financial flexibility and can therefore serve as a more adjustable payout channel under heightened uncertainty.

5.7 Control Variables

In addition to the main variables of interest, the analysis includes a set of standard firm-level controls commonly used in the payout literature (e.g., Attig et al., 2021; Fama and French, 2001). These controls include firm size ($Size$), profitability (ROA), retained earnings scaled by total assets (RE_TA), equity ratio ($Equity\_Ratio$), cash flow volatility ($CFVOL$), sales growth ($Sales\_Growth$), total cash holdings scaled by total assets ($Cash\_TA$), and GDP growth rate (GDP_Growth).

All firm-level control variables are lagged by one year to mitigate potential simultaneity between firm characteristics and payout decisions. Detailed variable definitions and data sources are reported in Table A3.

5.8 Summary Statistics

The following section presents descriptive statistics for the main variables used throughout the empirical analysis.

Table 1 reports summary statistics for the estimation sample. Mean total payout is 5.01% of assets, decomposed into repurchases (3.49%) and dividends (1.47%), consistent with the growing dominance of repurchases in the U.S. corporate payout policy (Brav et al., 2005). The larger standard deviation of repurchases relative to dividends confirms repurchases as the more flexible payout channel.

The weather variables exhibit substantial cross-state variation. Raw weather count averages 235 events per state-year (SD = 176), partly driven by high-exposure states such as Texas and Florida. The log transformation reduces skewness considerably (mean= 4.95, SD = 1.53), supporting the log specification used throughout. The threshold-based severity variables are substantially sparser by construction with events exceeding $10M average 1.39 per state-year, declining to 0.51 at >$50M, 0.35 at >$100M, and 0.11 at >$500M.

Approximately 20.3% of firm-year observations are classified as carbon-intensive under the baseline 4-digit SIC classification. This suggests that the baseline classification identifies a comparatively narrow and conservative subset of climate-vulnerable firms while still providing meaningful cross-sectional variation for the heterogeneity analysis.

The emissions-based carbon-intensity measure is available for a smaller subsample of 4,752 firm-year observations because Scope 1 and 2 disclosure is concentrated among larger firms among larger firms and later sample years. Raw emissions are heavily right-skewed (mean ≈ 498,000 metric tons CO_2; max = 17.76m), supporting the log transformation used in emission-based specifications. The narrow CPU index has a mean of 2.72 (SD = 1.46), indicating meaningful time-series variation in CPU across the sample period.

Table 2 reports pairwise correlations for the main variables. Repurchases correlate more strongly with total payouts (0.932) than dividends (0.498), confirming repurchases as the primary driver of aggregate payout variation. The weather variables are positively intercorrelated, indicating they capture related but distinct dimensions of local weather exposure, while their weak correlations with payout measures are consistent with heterogeneous firm-level responses. The 4-digit SIC carbon intensity indicator is negatively correlated with total payout (-0.194) and repurchases (-0.209) but not dividends (-0.026), consistent with more conservative payout behavior among carbon-intensive firms. The GHG intensity measure correlates modestly with the SIC classification (0.167), suggesting the two proxies capture related but not identical dimensions of carbon exposure.

Table 3 reports difference-in-means tests between carbon-intensive and non-carbon-intensive firms. Carbon-intensive firms exhibit substantially lower total payouts (3.09% vs 5.50% of assets), driven primarily by repurchases (1.50% vs 4.01%), while dividend payouts are marginally higher (1.58% vs 1.45%). This pattern is consistent with carbon-intensive firms relying less on flexible repurchases while maintaining stable dividend distributions. Carbon-intensive firms also experience greater weather exposure across all measures, averaging 265 events per state-year versus 227 for non-carbon firms, with more frequent exposure to severe events exceeding $50M. Together, these differences confirm that carbon-intensive firms are meaningfully distinct from non-carbon firms in both payout behavior and physical climate exposure, motivating the interaction specification.

Table 4 reports the geographic distribution of weather exposure across the 20 states with the highest number of total weather episodes. The results indicate substantial geographic concentration in weather exposure, especially in Texas and California, which account for a disproportionately large share of total weather events. The threshold-based measures further reveal important differences in weather severity across states. Texas exhibits particularly high exposure to economically severe weather events, including events exceeding $50M and $100M in property damages, whereas several other states with comparatively high overall event counts experience significantly fewer severe disaster events. This variation supports the interpretation that the weather measures capture meaningful differences in localized physical climate exposure rather than uniform national trends.

At the same time, this geographic concentration introduces possible omitted variable bias. Highly exposed states such as Texas and California represent economically large and important regions in the U.S. Consequently, simple pooled OLS estimations may be susceptible to omitted variable bias if regional economic conditions are correlated with both weather exposure and corporate payout behavior. Despite the concentration in several highly exposed states, the sample retains substantial geographic dispersion across firms and regions, with firms headquartered in states ranging from very high to comparatively moderate levels of weather exposure. This cross-sectional variation in localized weather shocks across firms and over time supports the identification strategy underlying the two-way fixed-effects framework employed in the empirical analysis.

Table 5 reports the industry distribution of the estimation sample across the major SIC industry groups. The table highlights substantial heterogeneity in payout behavior, localized weather exposure, and carbon intensity. Manufacturing, Transportation and Utilities, and

Agriculture and Mining exhibit the highest shares of carbon-intensive firms under the baseline 4-digit SIC classification. This pattern is broadly consistent with differences in industry-level emissions intensity as these industries also exhibit the highest average GHG intensity.

At the same time, payout behavior varies meaningfully across industries. Services and Wholesale and Retail exhibit relatively high average payout ratios, whereas Transportation and Utilities and Agriculture and Mining show lower average payouts. Weather exposure also differs substantially across industries, with Agriculture and Mining exhibiting particularly high average weather exposure. Overall, the industry distribution highlights meaningful cross-industry variation in payout behavior, weather exposure and climate vulnerability within the estimation sample.

Table 6 reports the distribution of firm-year observations across the sample period. The number of observations increases steadily over time from 751 observations in 2008 to 1,101 in 2024, reflecting changes in the S&P 1500 composition as well as gradually improving data availability throughout the sample period. The slight decline in observations in 2025 likely reflects incomplete data availability at the time of sample construction.

6. Empirical Framework

6.1 Baseline Empirical Specification

To examine the relationship between localized extreme weather exposure and corporate payout policy, we estimate a series of two-way fixed-effects (TWFE) panel regressions using firm-year observations for U.S. S&P 1500 firms from 2008 to 2025. The baseline specification is as follows:

$$Payout_{it} = \beta_1 \ln W_{st}^{(k)} + \beta_2 X_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Here, payout alternatively refers to total payouts, dividends, or share repurchases scaled by total assets for firm i in year t. $W_{st}^{(k)}$ measures localized weather exposure in the headquarters state s of firm i in year t, while X_{it-1} represents the vector of lagged firm-level control variables (see Appendix A3).

Firm fixed effects α_i control for time-invariant firm characteristics, while year fixed effects γ_t absorb aggregate macroeconomic shocks common across firms within a given year. Standard errors ε_{it} are clustered at the firm level to account for serial correlation.

6.2 Weather Exposure and Severity Specifications

To examine whether payout responses differ across CPU and firm-level climate vulnerability, we extend the baseline model by introducing interaction terms for climate policy and carbon intensity.

$$Payout_{it} = \beta_1 \ln W_{st}^{(k)} + \beta_2 (W_{st}^{(k)} \times \ CPU_t) + \ \beta_3 (\ln W_{st}^{(k)} \times \ Carbon_i) \ + \beta_4 X_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it}$$

Here, CPU_t represents the annual U.S. CPU index developed by Gavriilidis (2021), while $Carbon_i$ identifies the carbon intensity of firms using the baseline 4-digit SIC classification. The interaction terms examine whether the relationship between localized weather exposure and payout policy differs systematically between carbon-intensive and non-carbon-intensive firms as well as across periods of elevated climate policy uncertainty.

A key identification advantage of this design is that the weather variable varies at the state-year level, whereas a macro variable like CPU varies at the national-year level. Consequently, the standalone effect of CPU is absorbed by year fixed effects, while the interaction term remains identified through within-year cross-sectional variation in localized weather exposure across firms.

The empirical analysis distinguishes between overall weather exposure and economically severe weather shocks. The first set of specifications uses the logarithm of weather episode counts to capture broad weather exposure across firm headquarters states. The second set replaces the weather-count measure with threshold-based severity measures constructed using damage thresholds of $10M, $50M, $100M and $500M. This approach allows us to distinguish between routine weather exposure and economically material disasters.

All weather variables are specified in logarithmic standardized form. Therefore, the estimated coefficients can be interpreted as the effect of a one-standard-deviation increase in weather exposure or weather-shock severity on payout policy.

6.3 Intensive and Extensive Margin Analysis

In addition to the baseline regression models, we distinguish between intensive and extensive margins of corporate payout policy. The intensive margin analysis examines how much firms distribute conditional on making a payout and uses the continuous payout measures within the TWFE OLS framework.

The extensive margin analysis complements this by examining whether firms make any payout following localized weather shocks. For this purpose, we construct binary indicator variables equal to one if a firm conducts any payout during year t. The extensive-margin models are estimated using both a linear probability model with firm and year fixed effects and a probit model with industry and year fixed effects. The analysis focuses primarily on the threshold-based severity specifications, as economically severe disaster events are more likely to generate material payout adjustments than routine weather events.

7. Empirical Analysis

7.1 Weather Count Results

Table 7 reports the results of the weather-count models using standardized log-transformed weather exposure. All coefficients can therefore be interpreted as the payout effect associated with a one-standard-deviation increase in local weather exposure. In M1, the baseline weather coefficient is insignificant across all payout measures, suggesting no detectable average payout response when firms are pooled together. This baseline insignificance is consistent with opposing directional responses across firm types canceling out in the aggregate, motivating the richer interaction specifications that follow.

M2 introduces the full specification with both interaction terms. The baseline coefficient for non-carbon-intensive firms becomes positive and significant for both total payouts (0.704**) and repurchases (0.718***), while the interaction term for carbon-intensive firms is negative and statistically significant across both payout measures (–1.052*** and -0.869***). Dividend specifications (M3) remain insignificant throughout. Similarly, the interaction between weather exposure and CPU is insignificant across all specifications. Overall, the results indicate substantial heterogeneity across payout channels and firms. These results are also stronger under the logarithmic weather specification than under the raw event-count specification, suggesting that the proportional intensity of weather exposure rather than the absolute number of events represents the economically more relevant dimension of shock exposure.

Several aspects of these results warrant economic interpretation. The insignificant average baseline effect in M1 suggests that localized weather shocks are not associated with uniform payout reductions across the sample. As discussed in section 2.3 and 2.5, firms' net financial exposure to localized weather events depends substantially on insurance coverage, access to recovery liquidity, the availability of post-disaster financing, and broader financial resilience. Consequently, weather shocks affecting the headquarters state may not generate sufficient liquidity pressure to alter payout behavior among all firms.

The positive repurchase response among non-carbon-intensive firms is consistent with two mechanisms developed in the theoretical framework. First, financially resilient firms may maintain or increase repurchases following local weather shocks to signal balance-sheet strength and preserve investor confidence, consistent with the broader signaling literature on repurchases (Allen and Michaely, 2003; Skinner, 2008).

Second, insurance payouts, reconstruction spending, and disaster-related recovery liquidity may partially offset local operating disruptions, reducing the need to preserve internal cash holdings through lower distributions. The absence of significant dividend effects is further consistent with the dividend-stickiness literature discussed in Section 2.4, which argues that managers are typically reluctant to cut dividends and instead adjust through the more flexible repurchase channel (Brav et al., 2005; Jagannathan et al., 2000; Lintner, 1956).

The weather-count model uses the broader 1-digit SIC classification for carbon-intensity. Under the more granular 4-digit SIC classification, the interaction term attenuates and loses significance, suggesting that broad weather-count exposure may capture average weather events too imprecisely to identify sharper cross-sectional differences across industries. As shown in Section 7.2, these differences become substantially clearer once financially material damage thresholds are applied.

7.2 Weather Severity Results

Results for the weather severity models are reported in Tables 8 and 9. Table 8 shows the baseline model results across all thresholds, while Table 9 reports the interaction models including the 4-digit carbon-intensity classification and CPU. The baseline results in Table 8 reveal a clear threshold progression. At >\$10 million and >\$50 million damage thresholds, the weather coefficients remain insignificant across total payouts, dividends, and share repurchases, indicating no detectable average payout response to moderate damage events. At the >\$100 million threshold, however, the coefficient becomes positive for both total payout (0.073**) and repurchases (0.064*), while dividend effects remain insignificant throughout.

Introducing the interaction terms in Table 9 reveals that these positive baseline effects are concentrated among non-carbon-intensive firms. At the >\$50M threshold, the baseline coefficient for non-carbon-intensive firms is positive and significant for both total payouts (0.199*) and repurchases (0.187**), strengthening further at the >\$100M threshold for total payouts (0.250**) and repurchases (0.210**). In contrast, the interaction terms for carbon-intensive firms are negative and statistically significant at both thresholds for total payouts (-0.143** and -0.110*) and repurchases (-0.132* and -0.106*). Dividend interaction terms remain insignificant throughout. Similarly, the CPU interaction terms are insignificant across nearly all thresholds, with the exception of a marginally significant but economically small coefficient at >$100M (-0.05*). At the >$500m threshold, coefficients remain directionally positive but lose statistical insignificance.

The threshold progression in Table 8 is informative in itself. The absence of any significant effect at lower damage thresholds, followed by emergence of significant payout responses at the >$100M threshold, is consistent with the severity-conditioned logic developed in Section 3.3. Moderate weather events appear to generate insufficient financial disruption to alter average payout behavior, whereas financially material disasters are more likely to trigger liquidity pressures, recovery mechanisms, and managerial reassessment of shareholder distributions. This threshold pattern further suggests that results are unlikely to be driven solely by broad regional economic conditions correlated with weather activity, as such effects would be expected to appear at lower thresholds as well.

Once firm heterogeneity is introduced in Table 9, the positive response at the >$100M threshold is revealed as being concentrated among non-carbon-intensive firms. While precautionary theory would generally predict payout reductions following severe local shocks, the positive repurchase response among non-carbon-intensive firms is consistent with the alternative recovery and signaling mechanisms discussed in Sections 2.3 and 2.5. Firms with sufficient financial resilience, insurance coverage, or access to recovery liquidity may not need to reduce shareholder distributions following extreme weather exposure and may instead maintain or increase repurchases to signal financial strength. Overall, the results suggest that financially material weather shocks, rather than routine events, drive the observed payout responses.

The headquarter-based matching likely reinforces this interpretation. For geographically diversified firms, headquarters-state exposure may capture local managerial salience and regional economic disruption rather than direct operational destruction, potentially reducing the need for precautionary payout reduction.

Carbon-intensive firms respond significantly differently. Their attenuated or null response relative to non-carbon-intensive firms is consistent with the compounding vulnerabilities discussed in Sections 2.2 and 3.4, including greater physical exposure, tighter financing conditions, and heightened investor scrutiny. These factors may reduce both the capacity and willingness of carbon-intensive firms to sustain flexible distributions following a severe weather shock. Dividend stickiness remains evident across all thresholds, consistent with Section 2.4 and Lintner (1956), further confirming that repurchases represent the primary adjustment margin.

The consistent insignificance of the CPU interaction terms across severity thresholds reinforces the conclusion from Section 7.1 that physical and transition-related risks appear to operate through separate channels in the payout context. The insignificant results at the >$500m threshold should be interpreted in light of the underlying sample properties. This threshold captures only 7.1% of firm-year observations, with approximately 60% of observations concentrated in Texas and California and more than half occurring in 2017-2018, coinciding with Hurricanes Harvey, Irma, and Maria. The resulting reduction in statistical power limits reliable inference at this extreme threshold, although coefficient signs remain broadly consistent with the lower-threshold results.

The controls variables are broadly consistent with theoretical predictions and prior empirical findings across both the weather-count models (Table 7) and the severity-threshold models (Tables 8 and 9), supporting the overall specification of the empirical models. As the control variables remain stable across specifications, they are discussed collectively rather than separately for each model.

Firm size enters positively and significantly throughout, consistent with larger firms having greater financial capacity to sustain distributions. Profitability (ROA) is consistently positive and highly significant across all specifications, indicating that the more profitable firms distribute substantially more cash to shareholders, consistent with the free-cash-flow hypothesis (Jensen, 1986) and payout literature suggesting that mature and profitable firms are more likely to return cash to investors (DeAngelo et al., 2006). Retained earnings also enter positively and significantly, suggesting that more mature firms with greater accumulated profitability are more likely to distribute cash (Fama and French, 2021).

By contrast, cash-flow volatility enters negatively and significantly across most specifications, consistent with precautionary-liquidity arguments suggesting that firms facing greater earnings uncertainty conserve internal funds and reduce distributions (Chay and Suh, 2009). Cash holdings are positively associated with repurchases, reflecting that firms with greater liquidity buffers possess greater capacity to distribute cash. Finally, GDP growth enters positively in most specifications, consistent with the procyclical nature of corporate payout policy.

7.3 Intensive and Extensive Margin Results

Table 10 reports the intensive-margin results conditional on firms making positive payouts in a given year. At the >$10M threshold, the carbon interaction remains economically small and statistically insignificant. At the >$50M threshold, the baseline coefficient for non-carbon-intensive firms becomes positive and significant for total payouts (0.213*), while the carbon interaction term turns negative and significant (-0.150*). The strongest results emerge at the >$100M threshold. The baseline coefficient for non-carbon-intensive firms increases to 0.276**, while the carbon interaction term strengthens further to -0.166***, representing the largest interaction effect observed across all specifications. This implies a net spread of approximately 0.44 percentage points in payout intensity between non-carbon-intensive and carbon-intensive firms following a one-standard-deviation increase in severe weather exposure. Consistent with earlier results, the effect is concentrated in the repurchase channel, while dividend specifications remain insignificant throughout.

Table 11 reports the extensive-margin results. In the linear probability models, weather coefficients remain small and insignificant across all specifications. In the probit models, however, the interaction term between weather exposure and carbon intensity becomes positive and significant at the weather-count level (0.146**) and remains significant at the >$50M (0.090**) and >$100M (0.078**) thresholds. At the same time, the standalone carbon indicator remains strongly negative across all repurchase specifications (-0.282*** to -0.290***), indicating that carbon-intensive firms possess a structurally lower baseline propensity to conduct repurchases independent of weather exposure. Dividend participation effects remain insignificant throughout.

The intensive- and extensive-margin results confirm and sharpen the pattern identified in Section 7.2. The strengthening carbon differential at higher severity thresholds suggests that financially material weather shocks reveal meaningful differences in firm resilience and payout capacity. Among firms that continue to distribute cash, carbon-intensive firms reduce the scale of repurchases in years with catastrophic local weather exposure, while non-carbon-intensive firms increase repurchase intensity.

At the same time, the extensive-margin results reveal a complementary and important dimension. Although carbon-intensive firms reduce the scale of repurchases under severe weather exposure, they do not fully exit repurchase activity and may even become marginally more likely to conduct some repurchase activity following weather shocks. This distinction between the participation decision and the payout scale decision suggests that physical climate risk primarily affects the magnitude of repurchases rather than the decision to repurchase itself. One possible interpretation is that carbon-intensive firms preserve repurchase activity to maintain signaling flexibility and investor confidence while simultaneously reducing the amount distributed due to tighter financial constraints and greater climate-related vulnerability. Together, the intensive- and extensive-margin results reinforce the central finding of the thesis that payout responses to extreme weather are heterogeneous, concentrated in the repurchase channel, and strongly conditioned by carbon intensity.

7.4 Robustness Check: Single Firm Fixed Effects

As a robustness check on the two-way fixed-effects severity specifications, we re-estimate the multi-threshold damage models using firm fixed effects only, thereby allowing the standalone CPU effect to be identified rather than absorbed by year fixed effects. This specification relaxes the year fixed-effects structure at the cost of leaving aggregate macroeconomic shocks uncontrolled and therefore serves primarily as a robustness test of whether the main severity results depend on the two-way fixed-effects structure.

The results reported in Table 12 remain broadly consistent with the main findings. Across all three damage thresholds, the carbon-intensive interaction term remains negative and statistically significant for total payouts (-0.178**, -0.170**, -0.155**) and repurchases (-0.173**, -0.158**, and -0.143**), while dividend effects remain insignificant throughout. The pattern of increasing economic magnitude at higher severity thresholds is preserved, with the total payout coefficient strengthening from 0.100 at the >$10M threshold to 0.283*** at the >$100M threshold, closely mirroring the two-way fixed-effects results. Under this specification, the CPU interaction becomes separately identifiable. The coefficient is positive and significant at the >$10M and >$50M thresholds (both 0.017**) and turns negative and significant at the >$100M threshold (-0.058**), suggesting that heightened CPU may dampen payout responses. However, given the absence of year fixed effects and the resulting exposure to macroeconomic variation, these estimates should be interpreted cautiously.

7.5 Robustness Check: SA Index as Financial-Constraint Moderator

An alternative explanation for the weaker repurchase response among carbon-intensive firms is that it reflects underlying financial constraints rather than a genuine response to weather shocks. Summary statistics (Table 1) indicate that carbon-intensive firms hold roughly half the cash reserves of non-carbon-intensive firms, raising the possibility that financially constrained firms may reduce repurchases in response to adverse shocks more generally. To address this concern, we augment the baseline repurchase models with the Hadlock and Pierce (2010) SA index as a continuous moderator interacted with the weather variable. This allows us to test whether the weather-repurchase relationship is driven by financial-constraint intensity rather than carbon intensity itself. The key diagnostic is whether the carbon interaction term remains stable once the SA interaction is introduced.

As reported in Table 13, the carbon interaction coefficient is broadly stable across all specifications. At the >$50M threshold, the interaction changes only marginally from -0.116* to -0.126*, with a similarly stable pattern at the >$100M threshold. Importantly, the SA index interaction term remains insignificant across all specifications. This suggests that financial-constraint intensity does not systematically moderate the relationship between extreme weather exposure and repurchase behavior.

Overall, the results support the interpretation that the weaker repurchase response among carbon-intensive firms reflects differential climate-related vulnerability rather than a underlying financial-constraint channel, consistent with the compounding vulnerability mechanisms discussed in Sections 2.2 and 3.4.

7.6 Robustness Check: Alternative Dependent Variables Specifications

As an additional robustness check, we re-estimate the main severity threshold specifications using two alternative payout measures: the payout ratio (dividends scaled by net income) and dividend yield (dividends scaled by market capitalization). Results are reported in Tables 14 and 15. Neither alternative measure produces statistically significant results across the reported specifications. The payout-ratio results further suffer from a substantially reduced sample size (N = 9,429 versus 16,540 in the main models) due to the restriction to firm-years with positive net income.

The absence of significant results under these alternative specifications is not unexpected given their well-documented limitations. The payout ratio is mechanically sensitive to earnings volatility because both the numerator and denominator respond to earnings shocks, which potentially attenuates observable payout responses (Chay and Suh, 2009). Dividend yield additionally incorporates investor expectations and stock-price movements rather than purely managerial payout decisions (Brav et al., 2005). By contrast, total payouts scaled by total assets are less sensitive to earnings volatility and market-price fluctuations and therefore remain the preferred specification in the payout literature. Overall, the non-results under the alternative dependent variables do not materially alter the interpretation of the main findings.

7.7 Robustness Check: GHG-Based Carbon-Intensity Subsample

To address potential limitations of the 4-digit SIC-based carbon-intensity classification, we construct an alternative firm-level carbon-intensity measure using Scope 1 and 2 GHG emissions scaled by sales, consistent with Bolton and Kacperczyk (2021). The results reported in Table 16 yield no statistically significant coefficients across the reported specifications.

Two data limitations likely explain these non-results. First, the emissions-data availability restricts the sample period to 2017-2024, reducing the sample to 4,636 firm-year observations, less than one-third of the main sample. This substantially diminishes statistical power. Second, GHG-disclosure coverage is concentrated among larger firms subject to voluntary disclosure pressure, introducing selection bias that makes the subsample less representative of the broader estimation sample. Given these limitations, we retain the SIC-based carbon classification as our primary specification. The GHG-based results are reported primarily for transparency and as an exploratory firm-level emissions robustness test that future research with broader data coverage can build upon.

7.8 Robustness Check: Geographic Diversification

A central identification concern in our design is that headquarters-state exposure may not accurately capture operational exposure for geographically diversified firms. To address this concern, we merge annual foreign-sales data and split the sample using 25% and 50% foreign-revenue thresholds. If the estimated effects primarily reflect local physical exposure, payout responses should be stronger among domestically concentrated firms and attenuated for internationally diversified firms, consistent with Liu et al. (2025). Results are reported in Table 17.

Across all specifications and thresholds, no statistically significant results emerge, and no consistent directional pattern is observed. We attribute these non-results primarily to substantial sample attrition following the foreign-sales data merge, which reduces statistical power considerably, particularly within the diversified subsamples. The tests are therefore reported primarily for transparently regarding the headquarters-matching limitation rather than as conclusive evidence regarding geographic diversification effects.

Nevertheless, prior evidence by Custodio et al. (2025) documents a strong correlation of 0.86 between headquarters-based and establishment-level weather exposure measures, providing some reassurance that the headquarters proxy remains a reasonable approximation in the absence of establishment-level data.

7.9 Results Discussion

The results show that the relationship between extreme weather events and corporate payout policy is substantially more heterogeneous than precautionary motives alone would imply. Rather than observing uniform payout reductions following local weather shocks, payout responses depend on event severity, payout flexibility, and firm-level climate vulnerability. Financially material weather shocks are associated with positive payout responses, but these effects are concentrated primarily in the repurchase channel and differ systematically between carbon-intensive and non-carbon-intensive firms. Overall, the findings indicate that corporate payout responses to extreme weather events are shaped by the interaction between physical disruption, recovery liquidity, financial resilience, signaling motives, and payout flexibility.

The threshold progression observed across severity specifications indicates that financially material weather shocks, rather than routine weather events, represent the economically relevant dimension for corporate payout policy. Significant pooled payout effects only emerge at the >$100M threshold, consistent with prior climate-finance and catastrophe-risk literature emphasizing the importance of economic materiality in shaping corporate financial responses (Brown et al., 2021; Chen et al., 2023; Froot et al., 1993). Accordingly, the evidence provides only limited support for H1a but substantially stronger support for H1b, suggesting that payout responses to extreme weather events become economically meaningful primarily under highly severe disruptions.

The positive payout responses observed at the higher severity thresholds further indicate that realized extreme weather events do not uniformly translate into financial distress and precautionary payout reductions. Firms' net financial exposure to severe weather events depends strongly on insurance coverage, recovery liquidity, post-disaster financing capacity, and operational diversification. For financially resilient firms, these mechanisms likely help absorb localized disruptions and reduce pressure to preserve internal liquidity through lower shareholder distributions, consistent with Fan (2025) and Liu et al. (2025).

This interpretation is particularly relevant in the context of large publicly listed firms. Relative to smaller firms often studied in disaster-recovery settings, S&P 1500 firms may have greater access to external financing, larger liquidity buffers, more geographically diversified operations, and better access to insurance coverage, allowing them to absorb severe local disruptions without materially impairing payout capacity.

The results further complement and extend prior evidence on climate risk and corporate payout policy. Dessaint and Matray (2017) show that hurricane salience increases cash holdings and modestly reduces payout activity, while Chen et al. (2023) document that extreme rainfall exposure increases precautionary liquidity and lowers dividend payouts. In contrast, we find that sufficiently severe weather events are associated with positive payout responses concentrated primarily in repurchases rather than dividends, providing strong support for H2 and consistent with the view that firms adjust shareholder distributions mainly through the more flexible repurchase channel. The increase in share repurchases is also consistent with Chang et al. (2024), who show that climate risk is associated with higher repurchases but lower dividend payouts.

The contrast with Trinh (2025) is also informative. Trinh finds that longer-term climate exposure is associated with lower payouts, particularly among climate-vulnerable firms, but does not document robust substitution toward repurchases. By contrast, our evidence suggests that financially material weather shocks operate primarily through the repurchase channel, while dividend payouts remain largely insulated. This difference is consistent with the distinction between longer-term climate exposure and realized extreme weather events. Whereas chronic climate risk may gradually reduce firms' willingness to commit to long-term payouts, realized weather shocks appear to trigger more flexible and discretionary payout adjustments through repurchases.

Carbon intensity represents the central dimension of cross-sectional heterogeneity in the results and provides strong support for H3. The differential between carbon-intensive and non-carbon-intensive firms strengthens systematically as weather severity increases, particularly in the repurchase channel. While non-carbon-intensive firms exhibit significantly positive repurchase responses following financially material weather shocks, carbon-intensive firms respond substantially less positively and, in some specifications, offset the positive repurchase response observed among non-carbon-intensive firms. The intensive-margin results show that this differential persists conditional on firms actively distributing cash, indicating that carbon-intensive firms primarily reduce the scale rather than the likelihood of repurchase activity. The stability of the carbon interaction after controlling for the SA index further indicates that these effects are not solely driven by general financial-constraint intensity.

Overall, these findings imply that carbon-intensive firms face compounding climate-related vulnerabilities that constrain both the capacity and willingness to sustain flexible payouts following extreme weather events. This interpretation is consistent with prior climate-finance literature documenting tighter financing conditions and more conservative financial policies among carbon-intensive firms (Bolton and Kacperczyk, 2021; Cerón et al., 2024). The results extend prior climate-payout literature by showing that carbon intensity systematically conditions corporate payout responses to realized severe weather shocks.

Finally, the consistently insignificant CPU interaction terms suggest that CPU does not meaningfully moderate firms' payout responses to realized severe weather shocks. While prior literature documents important investment, financing, and payout effects of CPU, realized severe weather shocks appear to remain the economically more relevant driver of payout adjustments in the present setting. Accordingly, the findings provide no support for H4.

7.10 Limitations

While several identification and measurement concerns have already been discussed throughout Section 5 as well as the robustness analysis, this section briefly summarizes the remaining limitations of the empirical design.

First, the state-level aggregation of weather exposure introduces measurement error at the firm level, since firms within a state vary considerably in their proximity to the actual damage. This attenuation bias likely understates the true magnitude of the weather-payout relationship, meaning the effect sizes reported should be interpreted as lower bounds on firm-level exposure effects rather than precise estimates of operational impact.

Second, since repurchases can be adjusted relatively flexibly and at a higher frequency than dividends, the annual research design may not fully capture immediate adjustments in this payout channel. Firms may initially reduce repurchases after extreme weather events but subsequently increase them once recovery aid and insurance payments are received. Consequently, a quarterly research design may reveal different short-term adjustments that are not observable in annual data.

Third, the panel spans from 2008 to 2025 and includes structurally distinct periods like the Global Financial Crisis and COVID-19, which may generate heterogeneous treatment effects across time that our year fixed effects only partially absorb.

Fourth, while we control for the CPU index to separate physical weather effects from concurrent regulatory uncertainty, we cannot fully rule out that weather shocks and policy uncertainty are correlated in ways that make clean attribution difficult, particularly given that extreme weather events have become increasingly politicized.

8. Conclusion

This study examines how localized extreme weather events affect corporate payout policy among U.S. public firms. Using a panel of 16,540 S&P 1500 firm-year observations from 2008 to 2025, the analysis combines NOAA Storm Events data matched to firms by headquarters state with firm-level payout, financial, and carbon-intensity data to estimate a series of two-way fixed-effects models across alternative severity and payout specifications.

We find that, contrary to precautionary-liquidity arguments and prior climate-payout evidence predicting lower payouts following weather shocks, extreme weather events are not uniformly associated with reductions in corporate payout policy. Instead, payout responses are highly heterogeneous and depend on event severity, payout flexibility, and firm-level climate vulnerability. Significant payout effects emerge only following financially material weather shocks and are concentrated primarily in the repurchase channel, while dividend payouts remain comparatively stable. Moreover, non-carbon-intensive exhibit substantially more positive payout responses to severe weather shocks than carbon-intensive firms, suggesting that climate vulnerability systematically conditions corporate payout responses to realized weather shocks. The findings further indicate that firms with greater access to insurance coverage, recovery liquidity, external financing, and operational diversification may absorb severe localized disruptions without materially impairing payout capacity. Finally, climate policy uncertainty does not meaningfully moderate firms' payout responses to realized severe weather shocks.

These findings contribute to the literature in several ways. The study provides broader empirical evidence on the relationship between realized physical climate risk and corporate payout policy in the U.S. by examining a wide set of NOAA-defined climate-linked weather events rather than focusing on a single disaster type. Further, the study highlights payout flexibility and firm-level climate vulnerability as central dimensions shaping firms' responses to realized severe weather shocks. In particular, the results show that carbon intensity systematically moderates payout responses to extreme weather, contributing to the climate-finance literature on firm heterogeneity in the context of corporate payout policy. Finally, the analysis extends the literature by examining whether climate policy uncertainty moderates firms' payout responses to realized extreme weather events.

The findings also carry practical implications for corporate managers, investors, and ESG analysts. In particular, the findings suggest that payout responses become economically material primarily following financially material weather shocks, highlighting the importance of severe-event exposure for corporate payout planning and risk assessment. Further, the carbon heterogeneity findings may help investors and ESG analysts assess the financial resilience of climate-vulnerable firms under increasing physical climate risk.

This paper is not without limitations. Headquarters-state matching remains an imperfect proxy for firms' actual operational exposure, while the annual research design may not fully capture short-term payout adjustments, particularly in the repurchase channel. Further, although the findings suggest that insurance coverage, recovery liquidity, access to external financing, and operational diversification shape firms' responses to realized extreme weather events, these mechanisms cannot be directly identified within the current empirical design.

Future research could therefore benefit from more granular exposure measures, quarterly payout data, and international settings with different institutional and financial environments. Such extensions may provide additional insights into the mechanisms and external validity of the payout responses documented in this thesis.

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Empirical Tables

Table 1: Summary Statistics — Estimation Sample

Variable	N	Mean	Std. Dev.	p25	Median	p75	Min	Max
Panel A: Payout Variables								
Total Payout / Assets (%)	16540	5.013	6.493	0.750	2.630	6.708	0	35.705
Dividends / Assets (%)	16540	1.474	2.009	0	0.782	2.189	0	10.189
Repurchases / Assets (%)	16540	3.497	5.760	0.029	1.027	4.424	0	32.273
Panel B: Weather Exposure Variables								
Weather Episodes (count)	16540	234.9	176.1	124	210	274	0	948
Episodes >USD 10M damage	16540	1.380	2.160	0	1.230	2	0	16
Episodes >USD 50M damage	16540	0.510	1.119	0	0	1	0	9
Episodes >USD 100M damage	16540	0.354	0.882	0	0	0	0	5
Episodes >USD 500M damage	16540	0.111	0.460	0	0	0	0	4
Log weather count: log(1+N)	16540	4.949	1.526	4.828	5.352	5.617	0	6.855
Std. log weather count (z-score)	16540	0.000	1.000	-0.079	0.264	0.437	-3.242	1.249
Log weather >50M std (z-score)	16540	0.000	1.000	-0.554	-0.554	0.902	-0.554	4.283
Panel C: Carbon Intensity								
Scope 1+2 GHG Emissions (MT CO2e)	4752	498,120	1,292,999	20,566	87,021	377,258	0	17,760,000
GHG Intensity: Scope 1+2 / Sales	4752	38.176	79.003	5.028	13.434	33.605	0.096	576.448
Log GHG Intensity: log(1+Scope/Sales)	4752	2.722	1.323	1.796	2.670	3.544	0.091	6.359
=1 if GHG Intensity > Annual Median	4636	0.500	0.500	0	1	1	0	1
=1 if GHG Intensity > Annual 75th Pctile	4636	0.248	0.432	0	0	0	0	1

Panel D: Climate Policy Uncertainty								
CPU Narrow (100-pt units)	16540	2.716	1.461	1.535	1.977	3.786	1.176	6.722
CPU Broad (100-pt units)	16540	2.074	0.922	1.327	1.535	2.796	1.107	4.537
Carbon-Intensive (4-digit SIC)	16540	0.203	0.402	0	0	0	0	1
Panel E: Firm-Level Control Variables (lagged one year)								
Ln(Total Assets) [t−1]	16540	15.267	1.575	14.138	15.175	16.347	11.249	19.129
ROA [t−1]	16540	0.060	0.060	0.032	0.056	0.088	-0.293	0.237
RE / Assets [t−1]	16540	0.207	0.555	0.057	0.257	0.476	-3.109	1.318
Equity Ratio [t−1]	16540	0.418	0.235	0.282	0.420	0.570	-0.693	0.893
CF Volatility [t−1]	16540	0.042	0.035	0.018	0.032	0.055	0.004	0.181
Ln(Sales Growth) [t−1]	16540	0.069	0.188	-0.008	0.063	0.143	-0.592	0.784
Cash / Assets [t−1]	16540	0.141	0.152	0.032	0.089	0.196	0.001	0.753
GDP Growth (%) [t−1]	16540	2.058	1.889	1.819	2.512	2.793	-2.577	6.055

Notes: N = 16,540 firm-year observations, 2008–2025. Financial firms (SIC 6) excluded. Payout variables as % of total assets. Weather variables matched by firm HQ state from NOAA Storm Events Database. GHG sub-sample N = 4,752 (4,636 for indicators). CPU scaled to 100-pt units. Carbon-intensive defined using 4-digit SIC codes.

Table 2: Pearson Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Total Payout / Assets	1.000														
(2) Dividends / Assets	0.498	1.000													
(3) Repurchases / Assets	0.932	0.162	1.000												
(4) Log weather count (std)	0.054	-0.002	0.065	1.000											
(5) Log weather >50M (std)	0.020	-0.036	0.038	0.385	1.000										
(6) CPU narrow (scaled)	-0.030	-0.080	-0.005	0.049	0.029	1.000									
(7) Carbon-intensive (4d SIC)	-0.194	-0.026	-0.209	0.026	0.057	-0.036	1.000								
(8) GHG carbon high	-0.082	0.068	-0.116	-0.039	-0.079	0.001	0.167	1.000							
(9) Ln(total assets) [t−1]	0.050	0.193	-0.019	0.032	0.053	-0.062	0.095	0.034	1.000						
(10) ROA [t−1]	0.530	0.457	0.416	0.002	-0.019	-0.064	-0.157	-0.028	-0.023	1.000					
(11) RE/Assets [t−1]	0.167	0.268	0.077	-0.027	-0.070	-0.058	-0.065	0.069	0.109	0.373	1.000				
(12) Equity ratio [t−1]	-0.110	-0.188	-0.053	0.050	0.036	0.018	-0.029	-0.012	-0.238	0.032	0.280	1.000			
(13) CF volatility [t−1]	0.098	-0.080	0.142	0.043	0.098	0.113	-0.014	-0.084	-0.189	0.077	-0.142	0.047	1.000		
(14) Cash/Assets [t−1]	0.245	-0.073	0.305	0.031	0.076	0.023	-0.272	-0.200	-0.215	0.048	-0.106	0.201	0.336	1.000	
(15) GDP growth [t−1]	0.064	0.013	0.068	0.005	0.019	-0.091	-0.010	0.002	-0.002	0.092	-0.004	0.023	0.038	-0.021	1.000

Notes: Pearson correlations. Sample: 16,540 firm-year observations, 2008–2025. All variables as defined in Table 1.

Table 3: Difference-in-Means — Carbon-Intensive vs Non-Carbon-Intensive Firms

Variable	Non-Carbon Mean	Carbon Mean	Difference	t-stat	p-value	Sig.
Panel A: Payout Variables						
Total Payout / Assets (%)	5.501	3.090	−2.411	19.41	5.13e−83	***
Dividends / Assets (%)	1.447	1.580	0.133	−3.43	6.14e−4	***
Repurchases / Assets (%)	4.005	1.498	−2.508	22.86	7.20e−114	***
Panel B: Weather Exposure						
Weather Episodes (count)	227.334	264.631	37.297	−10.99	5.26e−28	***
Severe Weather Episodes	93.221	104.963	11.742	−9.70	3.51e−22	***
Episodes >USD 50M damage	0.480	0.626	0.146	−6.77	1.37e−11	***
Episodes >USD 100M damage	0.332	0.442	0.110	−6.45	1.14e−10	***
Std. log weather count (z-score)	−0.002	0.008	0.010	−0.50	0.618	
Log weather >50M std (z-score)	−0.026	0.101	0.127	−6.57	5.09e−11	***
Panel C: GHG Emissions (sub-sample)						
Scope 1+2 GHG Emissions (MT CO2e)	358,771	935,591	576,821	−13.41	2.88e−40	***
GHG Intensity: Scope 1+2 / Sales	23.999	82.684	58.685	−23.12	4.00e−112	***
Log GHG Intensity	2.526	3.339	0.814	−18.81	3.18e−76	***
=1 if GHG Intensity > Annual Median	0.453	0.647	0.194	−11.55	1.95e−30	***
=1 if GHG Intensity > Annual 75th Pctile	0.172	0.483	0.312	−22.22	5.20e−104	***
Panel D: Firm Characteristics [t−1]						
CPU Narrow (100-pt units)	2.735	2.645	−0.090	3.18	1.46e−3	***
Ln(Total Assets) [t−1]	15.117	15.857	0.740	−24.73	1.30e−132	***
ROA [t−1]	0.063	0.050	−0.012	10.70	1.26e−26	***
RE / Assets [t−1]	0.200	0.234	0.034	−3.16	1.56e−3	***
Equity Ratio [t−1]	0.428	0.381	−0.047	10.29	9.28e−25	***
CF Volatility [t−1]	0.044	0.038	−0.005	8.03	1.04e−15	***
Ln(Sales Growth) [t−1]	0.075	0.044	−0.031	8.51	1.97e−17	***
Cash / Assets [t−1]	0.161	0.062	−0.100	35.26	1.20e−262	***

*Notes: t-test of equality of means. *, **, *** = 10%, 5%, 1%. Carbon-intensive defined using 4-digit SIC codes. GHG sub-sample used for Panel C rows.*

Table 4: Top 20 States by Total Weather Episodes

State	Total Episodes	Severe Episodes	Ep. >$10M	Ep. >$50M	Ep. >$100M	Ep. >$500M	Mean Ep./Year
Texas	1,037,267	332,923	6,644	3,093	2,321	719	676.6
California	792,621	251,624	5,288	1,628	1,203	451	323.9
Illinois	214,268	77,512	1,474	474	352	43	261.0
New York	199,089	120,139	873	216	50	0	201.7
Pennsylvania	166,321	97,643	276	86	36	0	208.4
Florida	141,524	60,409	1,925	1,042	717	340	266.0
Ohio	130,040	93,164	532	150	113	37	185.5
Virginia	124,295	68,060	321	39	39	0	235.0
Georgia	104,262	61,394	463	148	124	0	213.7
North Carolina	82,719	44,182	464	220	156	16	265.1
Arizona	82,078	43,503	213	14	0	0	225.5
Minnesota	78,982	20,772	298	23	23	0	175.5
Colorado	75,467	12,492	261	147	126	23	236.6
Massachusetts	66,838	41,962	261	35	35	0	84.5
Missouri	62,444	24,659	289	125	83	29	250.8
Wisconsin	58,697	28,817	398	39	18	0	157.8
Tennessee	52,424	28,481	369	133	53	41	192.0
Michigan	45,482	23,644	493	160	59	19	122.9
New Jersey	44,108	13,562	228	107	80	42	95.7
Indiana	35,296	19,207	154	33	8	0	190.8

Notes: NOAA Storm Events Database, 2008–2025. Matched to firm HQ state. Damage thresholds in nominal USD.

Table 5: Sample Distribution by Industry

Industry Group	N Obs	% Sample	Mean Payout/TA	Mean Weather	% Carbon-Intensive	Mean GHG Int.
Agriculture & Mining (SIC 1)	1,065	6.4%	3.131	359.6	62.9%	48.21
Manufacturing (SIC 2)	3,040	18.4%	5.287	207.9	23.0%	53.00
Construction (SIC 3)	5,302	32.1%	4.668	217.3	7.4%	38.30
Transportation & Utilities (SIC 4)	2,133	12.9%	2.896	221.8	73.8%	42.06
Wholesale & Retail Trade (SIC 5)	1,851	11.2%	6.620	261.9	1.0%	14.70
Services (SIC 7)	2,364	14.3%	6.715	245.2	0.0%	31.15
Public Administration (SIC 8)	692	4.2%	5.669	240.6	0.0%	11.63
Other (SIC 9 / Unclassified)	93	0.6%	3.601	151.0	0.0%	42.86

Notes: Carbon-intensive defined using 4-digit SIC codes. GHG Intensity = Scope 1+2 / Sales. Financial firms (SIC 6) excluded.

Table 6: Sample Distribution by Year

Year	Observations	% of Sample	Cumulative %
2008	751	4.54%	4.54%
2009	768	4.64%	9.18%
2010	782	4.73%	13.91%
2011	794	4.80%	18.71%
2012	818	4.95%	23.66%
2013	834	5.04%	28.70%
2014	852	5.15%	33.85%
2015	879	5.31%	39.17%
2016	906	5.48%	44.64%
2017	943	5.70%	50.34%
2018	962	5.82%	56.16%
2019	983	5.94%	62.10%
2020	1,000	6.05%	68.15%
2021	1,024	6.19%	74.34%
2022	1,051	6.35%	80.70%
2023	1,080	6.53%	87.22%
2024	1,101	6.66%	93.88%
2025	1,012	6.12%	100.00%
Total	16,540	100.00%	

Table 7: Log Weather Count — Payout, Dividends, Repurchases

	Payout Baseline	Payout Full	Dividends	Repurchases
	(1)	(2)	(3)	(4)
Log weather count (std, z-score)	0.129	0.704**	−0.037	0.718***
	(0.217)	(0.331)	(0.094)	(0.275)
× CPU narrow (scaled)		−0.006	−0.001	−0.004
		(0.032)	(0.010)	(0.031)
× Carbon-intensive (4d SIC)		−1.052***	−0.119	−0.869***
		(0.405)	(0.124)	(0.329)
Ln(Total Assets) [t−1]	0.142	0.126	−0.167***	0.279*
	(0.176)	(0.174)	(0.050)	(0.161)
ROA [t−1]	28.564***	28.606***	4.286***	23.941***
	(2.271)	(2.263)	(0.575)	(2.083)
RE / Assets [t−1]	0.859**	0.857**	0.168*	0.708*
	(0.407)	(0.406)	(0.094)	(0.374)
Equity Ratio [t−1]	0.745	0.786	−0.349*	1.166*
	(0.658)	(0.663)	(0.185)	(0.627)
CF Volatility [t−1]	−14.190***	−14.160***	−1.984***	−11.883***
	(2.666)	(2.664)	(0.720)	(2.535)
Ln(Sales Growth) [t−1]	−0.777**	−0.769**	−0.231***	−0.535*
	(0.319)	(0.319)	(0.065)	(0.290)
Cash / Assets [t−1]	6.986***	7.020***	0.331	6.600***
	(0.966)	(0.961)	(0.226)	(0.907)
GDP Growth (%) [t−1]	−5.646***	−5.752***	0.596**	−6.253***
	(1.821)	(1.846)	(0.284)	(1.734)
Observations	16,540	16,540	16,540	16,540
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*Notes: Two-way FE (firm and year). Standard errors clustered at firm level in parentheses. Dependent variables as % of total assets. ln_wcount_std = standardised log(weather_count+1). *, **, *** = 10%, 5%, 1%.*

Table 8: Baseline Severity Threshold Models — Average Payout Effect

	Total Payouts				Dividends				Repurchases			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	>$10M	*>$50M*	*>$100M*	*>$500M*	*>$10M*	*>$50M*	*>$100M*	*>$500M*	*>$10M*	*>$50M*	*>$100M*	*>$500M*
Log weather >$10M (std, z-score)	0.015				0.008				0.007			
	(0.048)				(0.012)				(0.045)			
Log weather >$50M (std, z-score)		0.054				0.004				0.052		
		(0.042)				(0.010)				(0.040)		
Log weather >$100M (std, z-score)			0.073**				0.007				0.064*	
			(0.035)				(0.008)				(0.033)	
Log weather >$500M (std, z-score)				0.036				0.009				0.024
				(0.038)				(0.009)				(0.036)
Ln(Total Assets) [t−1]	0.142	0.140	0.140	0.143	−0.166***	−0.166***	−0.166***	−0.166***	0.293*	0.291*	0.291*	0.294*
	(0.176)	(0.176)	(0.176)	(0.176)	(0.050)	(0.050)	(0.050)	(0.050)	(0.163)	(0.163)	(0.163)	(0.163)
ROA [t−1]	28.578***	28.563***	28.569***	28.589***	4.267***	4.267***	4.267***	4.270***	23.936***	23.921***	23.928***	23.943***
	(2.268)	(2.267)	(2.267)	(2.268)	(0.575)	(0.575)	(0.575)	(0.576)	(2.089)	(2.088)	(2.088)	(2.089)
RE / Assets [t−1]	0.848**	0.849**	0.848**	0.848**	0.178*	0.178*	0.178*	0.178*	0.687*	0.689*	0.688*	0.688*
	(0.406)	(0.406)	(0.406)	(0.406)	(0.094)	(0.094)	(0.094)	(0.094)	(0.374)	(0.374)	(0.374)	(0.374)
Equity Ratio [t−1]	0.757	0.760	0.761	0.757	−0.363**	−0.363**	−0.362**	−0.363**	1.154*	1.157*	1.158*	1.154*
	(0.658)	(0.658)	(0.658)	(0.658)	(0.184)	(0.184)	(0.184)	(0.184)	(0.624)	(0.624)	(0.624)	(0.624)
CF Volatility [t−1]	−14.155***	−14.174***	−14.172***	−14.179***	−2.028***	−2.025***	−2.025***	−2.031***	−11.829***	−11.851***	−11.847***	−11.846***

	(2.667)	(2.665)	(2.664)	(2.665)	(0.719)	(0.719)	(0.719)	(0.719)	(2.538)	(2.537)	(2.536)	(2.536)
Ln(Sales Growth) [t−1]	−0.774**	−0.776**	−0.778**	−0.774**	−0.235***	−0.234***	−0.235***	−0.234***	−0.535*	−0.537*	−0.539*	−0.535*
	(0.319)	(0.320)	(0.320)	(0.320)	(0.066)	(0.066)	(0.066)	(0.066)	(0.290)	(0.290)	(0.290)	(0.290)
Cash / Assets [t−1]	6.987***	6.988***	6.992***	6.988***	0.329	0.328	0.329	0.329	6.570***	6.572***	6.576***	6.572***
	(0.967)	(0.967)	(0.967)	(0.967)	(0.225)	(0.225)	(0.225)	(0.225)	(0.910)	(0.910)	(0.910)	(0.910)
GDP Growth (%) [t−1]	−5.671***	−5.799***	−5.706***	−5.656***	0.561**	0.576**	0.581**	0.579**	−6.139***	−6.289***	−6.193***	−6.141***
	(1.825)	(1.822)	(1.822)	(1.821)	(0.279)	(0.280)	(0.278)	(0.279)	(1.712)	(1.708)	(1.708)	(1.708)
Observations	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: Two-way FE (firm and year). SEs clustered at firm level. Dependent variables as % of total assets. Each column uses the standardised log weather damage variable for that threshold (z-score). Controls lagged one year. *, **, *** = 10%, 5%, 1%.*

Table 9: Damage Threshold Models with Carbon-Intensity and CPU Interactions

	>$10M			>$50M			>$100M			>$500M		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
	Payout	*Divid.*	*Repurch.*	*Payout*	*Divid.*	*Repurch.*	*Payout*	*Divid.*	*Repurch.*	*Payout*	*Divid.*	*Repurch.*
Weather >$10M (std, z-score)	0.064	−0.001	0.059									
	(0.104)	(0.028)	(0.099)									
× CPU narrow (scaled)	0.001	0.005	−0.003									
	(0.032)	(0.009)	(0.031)									
× Carbon-intensive (4d SIC)	−0.141	−0.004	−0.138*									
	(0.089)	(0.028)	(0.079)									
Weather >$50M (std, z-score)				0.199**	−0.001	0.187**						
				(0.100)	(0.028)	(0.094)						
× CPU narrow (scaled)				−0.041	0.005	−0.040						
				(0.031)	(0.009)	(0.029)						
× Carbon-intensive (4d SIC)				−0.143*	−0.020	−0.132*						
				(0.076)	(0.022)	(0.069)						
Weather >$100M (std, z-score)							0.250**	0.020	0.210**			
							(0.100)	(0.029)	(0.094)			
× CPU narrow (scaled)							−0.050*	−0.003	−0.041			
							(0.030)	(0.008)	(0.028)			
× Carbon-intensive (4d SIC)							−0.110*	−0.009	−0.106*			
							(0.067)	(0.019)	(0.062)			

Weather >$500M (std, z-score)										−0.028	0.041	−0.071
										(0.130)	(0.028)	(0.122)
× CPU narrow (scaled)										0.036	−0.010	0.044
										(0.053)	(0.011)	(0.049)
× Carbon-intensive (4d SIC)										−0.092	−0.035*	−0.046
										(0.059)	(0.020)	(0.053)
Ln(Total Assets) [t−1]	0.140	−0.167***	0.291*	0.136	−0.167***	0.287*	0.136	−0.167***	0.287*	0.146	−0.166***	0.297*
	(0.176)	(0.050)	(0.163)	(0.176)	(0.050)	(0.163)	(0.176)	(0.050)	(0.163)	(0.176)	(0.050)	(0.163)
ROA [t−1]	28.597***	4.261***	23.961***	28.575***	4.262***	23.935***	28.559***	4.265***	23.917***	28.593***	4.264***	23.955***
	(2.265)	(0.575)	(2.086)	(2.267)	(0.575)	(2.087)	(2.267)	(0.575)	(2.088)	(2.269)	(0.576)	(2.090)
RE / Assets [t−1]	0.850**	0.178*	0.689*	0.844**	0.178*	0.684*	0.847**	0.178*	0.687*	0.850**	0.178*	0.688*
	(0.406)	(0.094)	(0.374)	(0.406)	(0.094)	(0.373)	(0.406)	(0.094)	(0.373)	(0.406)	(0.094)	(0.374)
Equity Ratio [t−1]	0.760	−0.361*	1.156*	0.765	−0.361*	1.161*	0.761	−0.362**	1.159*	0.758	−0.361*	1.154*
	(0.660)	(0.185)	(0.625)	(0.657)	(0.184)	(0.623)	(0.657)	(0.184)	(0.623)	(0.658)	(0.184)	(0.624)
CF Volatility [t−1]	−14.147***	−2.036***	−11.811***	−14.090***	−2.026***	−11.769***	−14.115***	−2.022***	−11.796***	−14.221***	−2.033***	−11.883***
	(2.671)	(0.720)	(2.543)	(2.664)	(0.720)	(2.536)	(2.665)	(0.720)	(2.537)	(2.665)	(0.720)	(2.535)
Ln(Sales Growth) [t−1]	−0.776**	−0.235***	−0.536*	−0.772**	−0.235***	−0.533*	−0.777**	−0.235***	−0.537*	−0.779**	−0.236***	−0.538*
	(0.319)	(0.066)	(0.290)	(0.319)	(0.066)	(0.290)	(0.320)	(0.066)	(0.290)	(0.319)	(0.066)	(0.290)
Cash / Assets [t−1]	6.996***	0.329	6.580***	7.013***	0.327	6.597***	7.022***	0.331	6.601***	6.992***	0.330	6.575***
	(0.967)	(0.225)	(0.910)	(0.968)	(0.225)	(0.910)	(0.967)	(0.225)	(0.910)	(0.968)	(0.225)	(0.911)
GDP Growth (%) [t−1]	−5.804***	0.500*	−6.209***	−5.543***	0.546*	−6.031***	−5.658***	0.582**	−6.153***	−5.982***	0.654**	−6.525***
	(1.836)	(0.284)	(1.722)	(1.811)	(0.280)	(1.696)	(1.818)	(0.278)	(1.704)	(1.883)	(0.296)	(1.757)
Observations	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: Two-way FE (firm and year). SEs clustered at firm level. Each group of three columns uses a separate damage-threshold weather variable with CPU and carbon interactions. All weather measures standardised. Controls lagged one year. *, **, *** = 10%, 5%, 1%.*

Table 10: Intensive Margin — Multi-Threshold Damage Models

	Total Payouts			Dividends			Repurchases		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log Weather >$10M (std, z-score)	0.059			0.012			0.042		
	(0.103)			(0.026)			(0.099)		
× CPU narrow (scaled)	-0.005			0.003			-0.007		
	(0.030)			(0.008)			(0.029)		
× Carbon-intensive (4d SIC)	-0.070			-0.031			-0.038		
	(0.089)			(0.022)			(0.084)		
Log Weather >$50M (std, z-score)		0.213*			0.003			0.196*	
		(0.113)			(0.030)			(0.106)	
× CPU narrow (scaled)		−0.035			0.005			−0.034	
		(0.034)			(0.009)			(0.032)	
× Carbon-intensive (4d SIC)		−0.151*			−0.031*			−0.121	
		(0.077)			(0.018)			(0.073)	
Log Weather >$100M (std, z-score)			0.276**			0.026			0.227**
			(0.107)			(0.030)			(0.101)
× CPU narrow (scaled)			−0.047			−0.003			−0.036
			(0.031)			(0.009)			(0.029)
× Carbon-intensive (4d SIC)			−0.166***			−0.024			−0.138**
			(0.064)			(0.015)			(0.061)
Ln(Total Assets) [t−1]	0.140	0.134	0.133	−0.167***	−0.167***	−0.167***	0.293*	0.286*	0.285*
	(0.176)	(0.176)	(0.176)	(0.050)	(0.050)	(0.050)	(0.163)	(0.163)	(0.163)

ROA [t−1]	28.584***	28.558***	28.546***	4.266***	4.262***	4.263***	23.943***	23.919***	23.908***
	(2.268)	(2.265)	(2.264)	(0.575)	(0.575)	(0.575)	(2.089)	(2.086)	(2.085)
RE / Assets [t−1]	0.851**	0.854**	0.855**	0.179*	0.179*	0.179*	0.689*	0.693*	0.694*
	(0.406)	(0.405)	(0.405)	(0.094)	(0.094)	(0.094)	(0.374)	(0.373)	(0.373)
Equity Ratio [t−1]	0.754	0.761	0.764	−0.363**	−0.361*	−0.362*	1.152*	1.158*	1.160*
	(0.659)	(0.658)	(0.658)	(0.184)	(0.184)	(0.184)	(0.625)	(0.624)	(0.624)
CF Volatility [t−1]	−14.141***	−14.098***	−14.119***	−2.028***	−2.018***	−2.019***	−11.816***	−11.786***	−11.804***
	(2.671)	(2.664)	(2.663)	(0.719)	(0.718)	(0.719)	(2.543)	(2.536)	(2.535)
Ln(Sales Growth) [t−1]	−0.775**	−0.774**	−0.774**	−0.235***	−0.235***	−0.234***	−0.535*	−0.535*	−0.536*
	(0.319)	(0.319)	(0.319)	(0.066)	(0.066)	(0.066)	(0.290)	(0.290)	(0.290)
Cash / Assets [t−1]	6.987***	6.993***	7.005***	0.329	0.325	0.329	6.571***	6.579***	6.586***
	(0.967)	(0.967)	(0.967)	(0.225)	(0.225)	(0.225)	(0.910)	(0.910)	(0.910)
GDP Growth (%) [t−1]	−5.671***	−5.652***	−5.724***	0.540*	0.551*	0.578**	−6.123***	−6.144***	−6.208***
	(1.820)	(1.811)	(1.820)	(0.278)	(0.281)	(0.278)	(1.707)	(1.696)	(1.706)
Observations	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold	>$10M	>$50M	>$100M	>$10M	>$50M	>$100M	>$10M	>$50M	>$100M

*Notes: Two-way FE (firm and year). Dependent variables as % of total assets. Weather variables are standardised log damage-threshold counts (z-score). Carbon = 4-digit SIC. Controls lagged one year. *, **, *** = 10%, 5%, 1%.*

Table 12: Robustness — Single Firm FE Multi-Threshold Damage Models

	>$10M			>$50M			>$100M		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Payout	*Divid.*	*Repurch.*	*Payout*	*Divid.*	*Repurch.*	*Payout*	*Divid.*	*Repurch.*
Log weather >$10M (std, z-score)	0.100			−0.053**			0.146		
	(0.098)			(0.026)			(0.093)		
× CPU narrow (scaled)	−0.008			0.017**			−0.024		
	(0.031)			(0.008)			(0.030)		
× Carbon-intensive (4d SIC)	−0.178**			−0.006			−0.173**		
	(0.086)			(0.027)			(0.077)		
Log weather >$50M (std, z-score)		0.198**			−0.043*			0.228**	
		(0.096)			(0.026)			(0.090)	
× CPU narrow (scaled)		−0.040			0.017**			−0.051*	
		(0.030)			(0.008)			(0.028)	
× Carbon-intensive (4d SIC)		−0.170**			−0.023			−0.158**	
		(0.075)			(0.021)			(0.068)	
Log weather >$100M (std, z-score)			0.283***			−0.009			0.273***
			(0.097)			(0.026)			(0.091)
× CPU narrow (scaled)			−0.059**			0.005			−0.058**
			(0.029)			(0.008)			(0.027)
× Carbon-intensive (4d SIC)			−0.155**			−0.020			−0.143**
			(0.065)			(0.019)			(0.060)

CPU narrow (100-point units)	0.177***	0.173***	0.174***	0.059***	0.059***	0.057***	0.108***	0.105***	0.107***
	(0.043)	(0.043)	(0.043)	(0.014)	(0.014)	(0.014)	(0.040)	(0.039)	(0.039)
Ln(Total Assets) [t−1]	0.341**	0.341**	0.339**	−0.005	−0.004	−0.002	0.332**	0.330**	0.326**
	(0.152)	(0.152)	(0.152)	(0.042)	(0.041)	(0.042)	(0.140)	(0.140)	(0.140)
ROA [t−1]	28.697***	28.669***	28.651***	4.259***	4.274***	4.278***	24.095***	24.049***	24.028***
	(2.174)	(2.175)	(2.176)	(0.544)	(0.544)	(0.544)	(2.007)	(2.008)	(2.010)
RE / Assets [t−1]	0.825**	0.817**	0.819**	0.195**	0.198**	0.197**	0.648*	0.638*	0.641*
	(0.393)	(0.392)	(0.392)	(0.095)	(0.094)	(0.095)	(0.361)	(0.361)	(0.361)
Equity Ratio [t−1]	0.715	0.723	0.721	−0.534***	−0.539***	−0.542***	1.281**	1.295**	1.296**
	(0.635)	(0.633)	(0.632)	(0.187)	(0.187)	(0.187)	(0.602)	(0.600)	(0.600)
CF Volatility [t−1]	−14.875***	−14.815***	−14.811***	−2.612***	−2.614***	−2.606***	−11.987***	−11.931***	−11.934***
	(2.484)	(2.476)	(2.476)	(0.692)	(0.691)	(0.691)	(2.370)	(2.362)	(2.362)
Ln(Sales Growth) [t−1]	−0.930***	−0.932***	−0.943***	−0.290***	−0.292***	−0.290***	−0.639**	−0.640**	−0.651**
	(0.298)	(0.298)	(0.298)	(0.064)	(0.064)	(0.064)	(0.270)	(0.270)	(0.271)
Cash / Assets [t−1]	7.659***	7.675***	7.688***	0.468**	0.464**	0.471**	7.087***	7.106***	7.111***
	(0.922)	(0.923)	(0.923)	(0.213)	(0.213)	(0.213)	(0.873)	(0.874)	(0.873)
GDP Growth (%) [t−1]	0.239***	0.238***	0.236***	0.048***	0.048***	0.048***	0.191***	0.190***	0.187***
	(0.021)	(0.021)	(0.021)	(0.005)	(0.005)	(0.005)	(0.018)	(0.019)	(0.019)
Observations	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540	16,540
Specification	Firm FE only	Firm FE only	Firm FE only	Firm FE only	Firm FE only	Firm FE only	Firm FE only	Firm FE only	Firm FE only
Threshold	>$10M	>$10M	>$10M	>$50M	>$50M	>$50M	>$100M	>$100M	>$100M

*Notes: Firm FE only (no year FE). CPU narrow and carbon_intensive separately identified. SEs clustered at firm level. Weather = standardised log(1+N episodes above threshold). 4-digit SIC carbon. Controls lagged one year. *, **, *** = 10%, 5%, 1%.*

Table 13: SA Financial Constraint as Continuous Moderator — Repurchases

	Log Count		>$50M		>$100M	
	(1)	(2)	(3)	(4)	(5)	(6)
	Base	*+SA Index*	*Base*	*+SA Index*	*Base*	*+SA Index*
Std. log weather count (z-score)	0.090	−0.004				
	(0.205)	(0.214)				
× Carbon-intensive (4d SIC)	−0.166	−0.140				
	(0.189)	(0.186)				
× SA Index (demeaned)		0.068				
		(0.185)				
Log weather >$50M (std, z-score)						
× Carbon-intensive (4d SIC)			−0.116*	−0.126*		
			(0.069)	(0.069)		
× SA Index (demeaned)				−0.037		
				(0.102)		
Log weather >$100M (std, z-score)					0.199**	0.194**
					(0.096)	(0.096)
× Carbon-intensive (4d SIC)					−0.092	−0.093
					(0.062)	(0.061)
× SA Index (demeaned)						0.004
						(0.090)
SA Index (demeaned)		3.080***		3.148***		3.125***
		(1.135)		(1.116)		(1.113)

Ln(Total Assets) [t−1]	0.269	0.509***	0.271	0.516***	0.271	0.514***
	(0.168)	(0.194)	(0.169)	(0.193)	(0.169)	(0.193)
ROA [t−1]	23.415***	23.971***	23.480***	24.053***	23.461***	24.026***
	(2.089)	(2.109)	(2.095)	(2.113)	(2.096)	(2.114)
RE / Assets [t−1]	0.656*	0.835**	0.635	0.822**	0.638	0.823**
	(0.389)	(0.401)	(0.388)	(0.401)	(0.388)	(0.400)
Equity Ratio [t−1]	1.265**	1.052	1.273**	1.050	1.270**	1.051
	(0.638)	(0.651)	(0.636)	(0.649)	(0.636)	(0.649)
CF Volatility [t−1]	−12.807***	−13.095***	−12.721***	−13.027***	−12.749***	−13.063***
	(2.636)	(2.635)	(2.639)	(2.640)	(2.640)	(2.639)
Ln(Sales Growth) [t−1]	−0.487	−0.501*	−0.488	−0.502*	−0.493	−0.507*
	(0.299)	(0.299)	(0.299)	(0.299)	(0.300)	(0.299)
Cash / Assets [t−1]	6.508***	6.493***	6.534***	6.521***	6.539***	6.524***
	(0.929)	(0.926)	(0.930)	(0.927)	(0.929)	(0.926)
GDP Growth (%) [t−1]	−6.188***	−6.760***	−6.319***	−7.032***	−6.452***	−7.163***
	(1.846)	(1.868)	(1.736)	(1.743)	(1.744)	(1.754)
Observations	15,665	15,665	15,665	15,665	15,665	15,665
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: Dependent variable: repurchases / total assets (%). Odd = baseline (weather × carbon). Even = adds SA index as continuous moderator. SA index: Hadlock & Pierce (2010), demeaned. Firm and year FE. SEs clustered at firm level. *, **, *** = 10%, 5%, 1%.*

Table 14: Robustness — Payout Ratio (Dividends/Net Income)

	Payout/TA (Reference)	Payout Ratio	Payout Ratio	Payout Ratio	Payout Ratio
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Payout/TA	*PR Baseline*	*PR Count*	*PR >$50M*	*PR >$100M*
Std. log weather count (z-score)	0.347	0.289			
	(0.228)	(1.503)			
× CPU narrow (scaled)	−0.019		0.004		
	(0.038)		(0.496)		
× Carbon-intensive	−0.442*		1.910		
	(0.259)		(2.773)		
Log weather >$50M (std, z-score)			−0.588		
			(1.412)		
× CPU narrow (scaled)			0.195		
			(0.422)		
× Carbon-intensive			0.417		
			(1.085)		
Log weather >$100M (std, z-score)				−0.223	
				(1.470)	
× CPU narrow (scaled)				0.091	
				(0.408)	
× Carbon-intensive				−0.323	
				(1.095)	
Ln(Total Assets) [t−1]	0.125	5.207**	5.274**	5.208**	5.187**

	(0.175)	(2.085)	(2.088)	(2.090)	(2.094)
ROA [t−1]	28.563***	−189.196***	−189.174***	−189.538***	−189.301***
	(2.267)	(23.511)	(23.431)	(23.427)	(23.414)
RE / Assets [t−1]	0.860**	10.585**	10.635**	10.524**	10.535**
	(0.404)	(4.606)	(4.595)	(4.615)	(4.609)
Equity Ratio [t−1]	0.780	−1.433	−1.761	−1.412	−1.375
	(0.660)	(8.008)	(8.065)	(7.998)	(7.995)
CF Volatility [t−1]	−14.079***	31.031	30.699	30.913	31.192
	(2.658)	(39.540)	(39.585)	(39.532)	(39.550)
Ln(Sales Growth) [t−1]	−0.760**	−17.216***	−17.267***	−17.193***	−17.193***
	(0.319)	(4.304)	(4.315)	(4.323)	(4.322)
Cash / Assets [t−1]	6.999***	19.292**	19.250**	19.295**	19.267**
	(0.964)	(9.172)	(9.159)	(9.165)	(9.167)
GDP Growth (%) [t−1]	−5.946***	13.378	13.641	12.665	13.634
	(1.884)	(23.313)	(23.267)	(23.579)	(23.295)
Observations	16,540	9,429	9,429	9,429	9,429
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

*Notes: Col 1: main model (Payout/TA) for reference. Cols 2–5: dependent = Dividends / Net Income, winsorised 1st/99th pctiles. Restricted to firm-years with positive net income (N=9,429). Firm and year FE. SEs clustered at firm level. *, **, *** = 10%, 5%, 1%.*

Table 15: Robustness — Dividend Yield (Dividends/Market Cap)

	(1)	(2)	(3)	(4)
	Baseline	*Count*	*>$50M*	*>$100M*
Std. log weather count (z-score)	0.203	0.386		
	(0.196)	(0.415)		
× CPU narrow (scaled)		−0.037		
		(0.033)		
× Carbon-intensive		−0.123		
		(0.380)		
Log weather >$50M (std, z-score)			0.122	
			(0.099)	
× CPU narrow (scaled)			−0.039	
			(0.025)	
× Carbon-intensive			0.023	
			(0.063)	
Log weather >$100M (std, z-score)				0.169*
				(0.097)
× CPU narrow (scaled)				−0.045*
				(0.026)
× Carbon-intensive				−0.030
				(0.056)
Ln(Total Assets) [t−1]	0.090	0.099	0.090	0.090
	(0.101)	(0.103)	(0.108)	(0.108)
ROA [t−1]	0.751	0.864	0.918	0.920
	(1.133)	(1.156)	(1.148)	(1.151)
RE / Assets [t−1]	0.557***	0.551***	0.510**	0.512**
	(0.214)	(0.207)	(0.234)	(0.231)
Equity Ratio [t−1]	0.157	0.174	0.136	0.126
	(0.378)	(0.388)	(0.372)	(0.371)
CF Volatility [t−1]	−3.183**	−3.216**	−3.010*	−3.023*
	(1.611)	(1.603)	(1.597)	(1.599)
Ln(Sales Growth) [t−1]	−0.043	−0.046	−0.041	−0.039
	(0.160)	(0.160)	(0.161)	(0.160)
Cash / Assets [t−1]	−0.795	−0.795	−0.775	−0.752

	(0.506)	(0.508)	(0.494)	(0.497)
GDP Growth (%) [t−1]	−0.034	−0.361	0.225	0.238
	(0.783)	(0.882)	(0.777)	(0.769)
Observations	3,165	3,165	3,165	3,165
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

*Notes: Dependent variable = annual dividends / market capitalisation (dividend yield). Firm and year FE. SEs clustered at firm level. N=3,165 due to market cap data availability. *, **, *** = 10%, 5%, 1%.*

Table 16: Robustness — GHG Sub-Sample, 2017–2024

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	Payout (Base)	*Payout (Median)*	*Dividends*	*Repurchases*	*Payout (Top 25%)*
Std. log weather count (z-score)	−0.128	−1.017	−0.672	0.063	−0.965
	(0.315)	(1.220)	(0.555)	(0.866)	(1.078)
× CPU narrow (scaled)		0.242	0.077	0.085	0.242
		(0.231)	(0.088)	(0.191)	(0.246)
× GHG carbon high (median)		0.135	0.381	−0.444	
		(0.652)	(0.318)	(0.446)	
× GHG carbon high (top 25%)					0.091
					(0.424)
=1 if GHG intensity > annual median		−0.823*	−0.262	−0.420	
		(0.425)	(0.160)	(0.338)	
=1 if GHG intensity > annual 75th pctile					−0.302
					(0.339)
Ln(Total Assets) [t−1]	0.657	0.634	−0.227**	0.869**	0.648
	(0.415)	(0.414)	(0.106)	(0.392)	(0.413)
ROA [t−1]	22.836***	22.278***	4.237***	17.592***	22.648***
	(4.284)	(4.249)	(0.947)	(4.174)	(4.281)
RE / Assets [t−1]	−0.152	−0.121	0.441**	−0.535	−0.159
	(1.087)	(1.088)	(0.211)	(1.038)	(1.092)
Equity Ratio [t−1]	4.645**	4.794**	0.114	4.805**	4.753**
	(2.012)	(2.008)	(0.344)	(1.887)	(2.020)
CF Volatility [t−1]	−15.403**	−15.388**	−1.095	−13.828**	−15.129**
	(5.999)	(6.075)	(1.889)	(5.776)	(6.078)
Ln(Sales Growth) [t−1]	0.956*	0.909	0.096	0.777	0.956*

	(0.562)	(0.564)	(0.116)	(0.535)	(0.562)
Cash / Assets [t−1]	7.741***	7.808***	−0.393	8.006***	7.736***
	(2.094)	(2.090)	(0.267)	(1.980)	(2.102)
GDP Growth (%) [t−1]	1.346***	1.373***	0.149**	1.117**	1.370***
	(0.504)	(0.501)	(0.067)	(0.477)	(0.502)
Observations	4,636	4,636	4,636	4,636	4,636
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Period	2017–2024	2017–2024	2017–2024	2017–2024	2017–2024

*Notes: Sample restricted to 2017–2024 (Scope 1+2 data). GHG carbon high = 1 if GHG intensity > annual median (cols 2–4) or 75th pctile (col 5). Firm and year FE. SEs clustered at firm level. *, **, *** = 10%, 5%, 1%.*

Table 17: Robustness — Alternative Foreign Sales Cutoffs

	(1) <25%	(2) ≥25%	(3) <50%	(4) ≥50%	(5) <25%	(6) ≥25%	(7) <50%	(8) ≥50%
Log weather >$50M (std, z-score)	−0.523	0.681	−0.528	0.473	−0.567	0.250	−0.568	0.152
	(0.592)	(2.065)	(0.586)	(2.034)	(0.544)	(2.069)	(0.538)	(2.098)
× CPU narrow (scaled)	0.183	−0.327	0.192	−0.418	0.186	−0.180	0.194	−0.320
	(0.184)	(0.620)	(0.182)	(0.684)	(0.175)	(0.607)	(0.173)	(0.692)
× Carbon-intensive (4d SIC)	−0.203	0.405	−0.226	0.700	−0.146	0.184	−0.169	0.751
	(0.193)	(1.135)	(0.192)	(1.283)	(0.181)	(0.998)	(0.179)	(1.230)
Ln(Total Assets) [t−1]	0.481	1.742	0.557	2.546	0.503	1.746	0.572	2.172
	(0.491)	(2.711)	(0.485)	(2.294)	(0.444)	(2.684)	(0.437)	(2.144)
ROA [t−1]	15.562***	46.568**	17.997***	−15.673	13.072***	32.791	15.359***	−23.622
	(4.797)	(21.790)	(5.174)	(26.017)	(4.212)	(19.590)	(4.649)	(22.914)
RE / Assets [t−1]	1.987*	11.787**	2.128*	−2.648	2.080**	12.770**	2.222**	−0.901
	(1.121)	(4.804)	(1.085)	(5.645)	(0.914)	(5.061)	(0.888)	(5.328)
Equity Ratio [t−1]	0.243	12.285***	−0.340	37.558***	−0.292	8.745**	−0.893	34.043***
	(1.797)	(4.482)	(1.757)	(8.131)	(1.432)	(4.273)	(1.454)	(7.096)
CF Volatility [t−1]	−18.332***	14.997	−19.280***	−18.596	−11.384*	15.094	−12.443*	−11.504
	(7.068)	(38.010)	(7.162)	(32.457)	(6.267)	(36.896)	(6.408)	(37.093)
Ln(Sales Growth) [t−1]	0.696	−1.054	0.488	3.912*	0.360	−0.282	0.157	4.236**
	(0.696)	(2.611)	(0.717)	(2.205)	(0.579)	(2.388)	(0.608)	(1.913)
Cash / Assets [t−1]	11.212***	19.669**	12.022***	9.401**	10.845***	18.935**	11.605***	8.886*
	(3.569)	(7.547)	(3.553)	(4.525)	(3.306)	(7.207)	(3.299)	(4.374)
GDP Growth (%) [t−1]	1.383	−1.072	1.337	1.560	1.339	−1.545	1.230	1.856
	(0.957)	(5.730)	(0.960)	(5.708)	(0.882)	(5.308)	(0.885)	(5.037)
Observations	2,369	145	2,401	113	2,369	145	2,401	113
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Foreign sales cutoff	<25%	≥25%	<50%	≥50%	<25%	≥25%	<50%	≥50%

*Notes: Dependent variables as % of total assets. Weather = standardised log of episodes >$50M damage. Sample split by foreign sales share. Firm and year FE. SEs clustered at firm level. *, **, *** = 10%, 5%, 1%.*

Figures

Figure 1: High-Damage Weather Episodes per State by Year

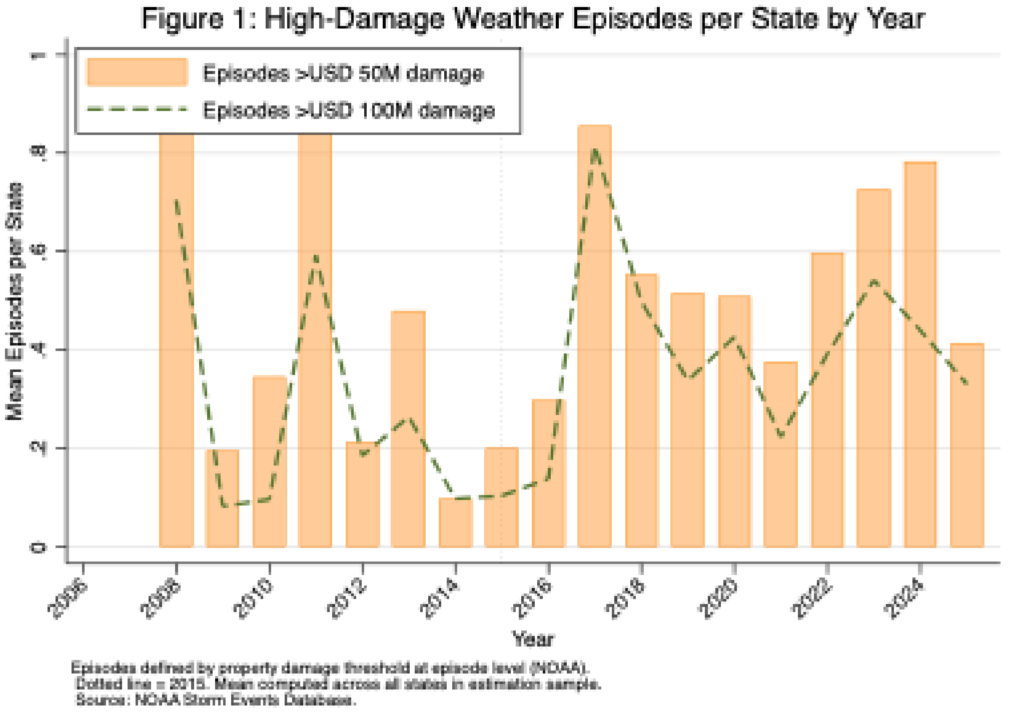

Figure 1 shows mean number of high damage events over the sample period per year. With the year on the x-axis and the mean episodes across all states in that year.

Figure 2: Mean Total Payout by Carbon Intensity, 2006 – 2025

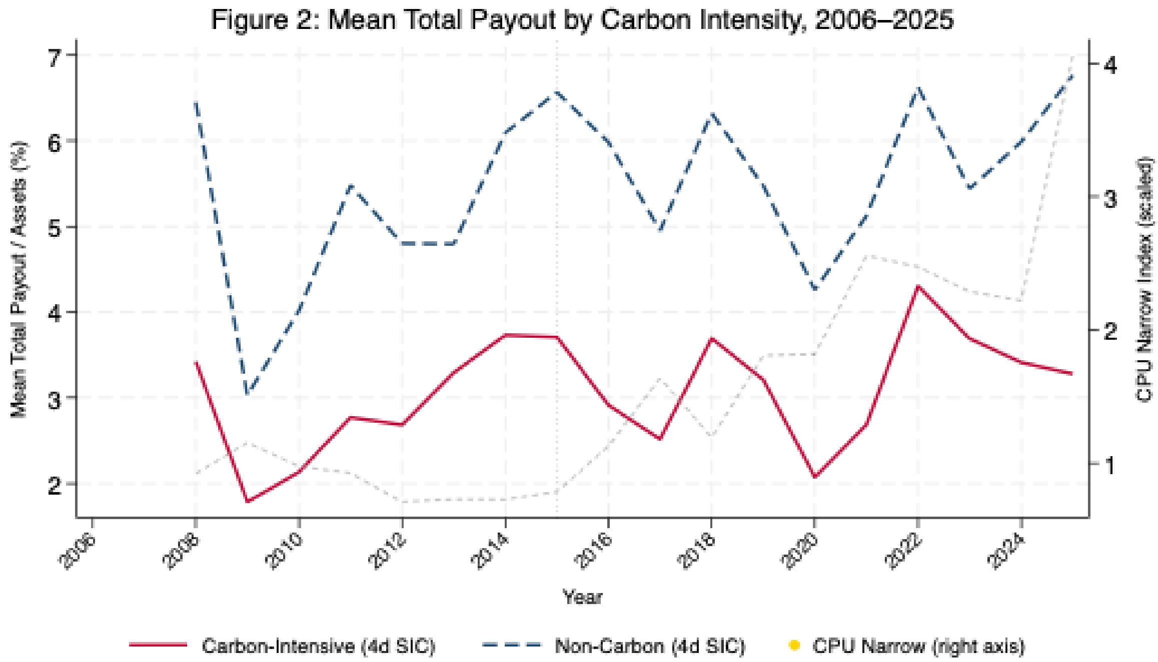

Figure 2 overlays mean payout for mean payout (left axis) for carbon-intensive vs non-carbon-intensive firms with the CPU index scaled on the right axis. Over the treated sample duration 2006-2025.

Appendix

Table A1: NOAA Event Type Classification — Climate Attribution

Event Type(s)	Climate Attribution Rationale	Status
Panel A: Climate-Linked Events — Included in Baseline		
Flash Flood; Flood; Coastal Flood; Lakeshore Flood	Intensified by heavier precipitation: warmer atmosphere holds more moisture, increasing flood frequency and magnitude (IPCC AR6, 2021).	Included
Heavy Rain	: ~7% more moisture per °C of warming increases extreme precipitation.	Included
Drought	Increased evapotranspiration and altered precipitation patterns under warming extend drought duration.	Included
Excessive Heat; Heat	Directly driven by global mean temperature increase; extreme heat events more frequent and intense (IPCC AR6).	Included
Wildfire	Warming produces longer fire seasons and drier conditions; attribution links increased fire weather to anthropogenic forcing.	Included
Tropical Storm; Hurricane; Marine Hurricane/Typhoon; Marine Tropical Storm	Warmer sea surface temperatures increase storm intensity and rainfall; proportion of category 4–5 storms has increased (Knutson et al., 2020).	Included
Storm Surge/Tide	Amplified by sea level rise, increasing inundation frequency and severity.	Included
Panel B: Included but Contested (robustness sensitivity)		
Tornado; High Wind; Thunderstorm Wind; Strong Wind	Attribution contested; included following Chang et al. (2024)..	Contested
Winter Storm; Blizzard; Ice Storm	Paradoxically intensified by warming-driven atmospheric instability. Flagged as contested; retained for robustness.	Contested
Panel C: Excluded — No Established Climate Attribution		
Hail	Natural process; weak and inconsistent climate signal.	Excluded
Frost/Freeze	Natural cold-weather event; no robust anthropogenic attribution.	Excluded
Dense Fog; Marine Dense Fog	No established link to anthropogenic climate change.	Excluded
Funnel Cloud; Waterspout	No ground contact / marine event; no firm-level economic impact.	Excluded
Dust Devil; Rip Current; Avalanche; Seiche; Sneakerwave	Local/oceanic/topographic phenomena; no climate attribution or firm impact.	Excluded
Astronomical Low Tide; Lightning; Lake-Effect Snow	Tidal, natural atmospheric, or regional phenomena; not climate-driven.	Excluded

Notes: Classification follows IPCC AR6 (2021) and the peer-reviewed climate attribution literature. Events in Panel B are retained in baseline but can be excluded as a robustness check. All event types sourced from NOAA Storm Events Database.

Table A2: Carbon-Intensive Industry Classification — 4-Digit SIC Codes

SIC Group	SIC Codes	Industry Description	Basis for Classification
Panel A: Extraction & Mining (SIC Division B)			
SIC 1–2	1000–1499	Coal Mining; Metal Mining — bituminous/anthracite coal, iron ore, copper, lead, zinc, gold, silver.	High direct GHG emissions from extraction and combustion; consistent with EPA and S&P Global carbon classifications.
SIC 1	1311–1389	Oil & Gas Extraction — crude petroleum and natural gas, natural gas liquids, field services.	Among the highest Scope 1 emission intensities; central to fossil fuel supply chain.
Panel B: Carbon-Intensive Manufacturing (SIC Division D)			
SIC 2	2600–2661	Paper & Allied Products — pulp mills, paper mills, paperboard mills.	Energy-intensive; included in EPA high-intensity sectors.
SIC 2	2810–2879	Industrial Chemicals & Allied Products — inorganic/organic chemicals, plastics, agricultural chemicals.	High process emissions; classified as carbon-intensive by S&P Global.
SIC 2	2911	Petroleum Refining — crude petroleum refining.	Extremely high Scope 1 emissions; core fossil fuel processing.
SIC 3	3200–3390	Primary Metals & Cement — stone, clay, glass, blast furnaces, steel works, smelters.	High-temperature processes produce substantial CO2 from energy use and process chemistry.
Panel C: Utilities (SIC Division E)			
SIC 4	4911–4959	Electric & Gas Utilities — electric services, gas distribution, combination utilities.	Direct combustion of fossil fuels; among the largest US GHG emitters.
Panel D: Carbon-Intensive Transportation (SIC Division E)			
SIC 4	4210–4215	Trucking & Warehousing — trucking and courier services.	High diesel consumption; included following EPA transport emission intensity rankings.
SIC 4	4400–4522	Air & Water Transportation — tankers, scheduled/non-scheduled air transportation, airports.	High fuel intensity per ton-mile; aviation and shipping significant emission sources (IPCC AR6).
Panel E: Fossil Fuel Wholesale Trade (SIC Division F)			
SIC 5	5170–5172	Petroleum & Petroleum Products Wholesale — bulk stations, terminals, petroleum dealers.	Direct involvement in fossil fuel distribution; consistent with S&P Global sector definitions.

Notes: Classification follows EPA emission intensity rankings and S&P Global carbon classifications. Financial firms (SIC 6000–6999) excluded from estimation sample.

Table A3: Variable Definitions

Variable	Definition	Source
Panel A: Dependent Variables		
Payout_TA	Total payout (dividends + repurchases) scaled by total assets × 100 (% of assets).	Capital IQ
Dividends_TA	Cash dividends paid scaled by total assets × 100.	Capital IQ
Repurchases_TA	Share repurchases scaled by total assets × 100.	Capital IQ
Pays_Anything	=1 if firm made any payout in year t; 0 otherwise. Used in probit models.	Capital IQ
Payout_NI	Total payout scaled by net income × 100. Restricted to positive net income observations.	Capital IQ
Panel B: Weather Exposure Variables		
ln_wcount_std	Standardised log weather count (z-score): log(1+N) where N = total NOAA episodes in HQ state-year, then z-score standardised.	NOAA Storm Events Database
ln_w10m_std	Standardised log count of episodes with property damage >$10M: log(1+N_10M), z-score standardised.	NOAA Storm Events Database
ln_w50m_std	Standardised log count of episodes with property damage >$50M: log(1+N_50M), z-score standardised.	NOAA Storm Events Database
ln_w100m_std	Standardised log count of episodes with property damage >$100M: log(1+N_100M), z-score standardised.	NOAA Storm Events Database
ln_w500m_std	Standardised log count of episodes with property damage >$500M: log(1+N_500M), z-score standardised.	NOAA Storm Events Database
Panel C: Climate Policy Uncertainty		
CPU_Narrow (scaled)	Annual mean of monthly narrow-measure CPU index / 100. One unit = 100-point change in the index (Gavriilidis, 2021).	policyuncertainty.com
CPU_Broad (scaled)	Annual mean of monthly broad-measure CPU index / 100. Used for robustness.	policyuncertainty.com
Panel D: Carbon Intensity Measures		
Carbon_Intensive	=1 if firm primary 4-digit SIC code falls in carbon-intensive sector (see Table A2); 0 otherwise.	Capital IQ; authors
GHG Intensity	Scope 1+2 GHG emissions / total sales (tons CO2e per USD million). Sub-sample of firms with voluntary disclosure.	Bloomberg ESG
Log GHG Intensity	log(1 + Scope1+2 / Sales). Addresses right-skew in raw GHG intensity.	Bloomberg ESG
GHG_High_Median	=1 if GHG intensity > annual cross-sectional median.	Bloomberg ESG
GHG_High_P75	=1 if GHG intensity > annual 75th percentile.	Bloomberg ESG

Panel E: Interaction Terms		
Weather × CPU	Weather (std) × CPU_Narrow (scaled). Tests whether CPU amplifies/attenuates payout response to weather shocks.	Authors
Weather × Carbon	Weather (std) × Carbon_Intensive. Tests differential payout response for carbon-intensive firms.	Authors
CPU × Carbon	CPU_Narrow × Carbon_Intensive. Tests whether CPU effect is stronger for carbon-intensive firms.	Authors
Panel F: Control Variables (all lagged one year, t−1)		
Size	log(Total Assets in USD millions).	Capital IQ
ROA	Net income / total assets.	Capital IQ
Retained Earnings	Retained earnings / total assets. Proxy for lifecycle stage (DeAngelo et al., 2006).	Capital IQ
Equity_Ratio	Total equity / total assets. Inverse leverage proxy.	Capital IQ
CFVol	Std. dev. of operating cash flows over rolling window. Measures financial uncertainty.	Capital IQ
Sales_Growth	log(Sales_t / Sales_{t-1}).	Capital IQ
Cash_TA	Cash and short-term investments / total assets.	Capital IQ
GDP_Growth	Annual % GDP growth rate. Macro control for business cycle.	World Bank WDI

Notes: All firm-level controls lagged one year. Payout variables × 100 (% of assets). Weather variables constructed from NOAA Storm Events Database matched to firm HQ state. CPU scaled to 100-pt units. Financial firms (SIC 6) excluded throughout.

AI Statement

Generative AI tools, specifically Claude and ChatGPT, were used to support several aspects of the thesis process. The tools were primarily used for language refinement, reducing the word count as well as structuring ideas and improving clarity. In addition, the mentioned AI tools were used to support with technical tasks in Stata.

All theoretical, methodological decisions, empirical analysis, interpretation of results, and conclusions were ultimately developed and evaluated by the authors, while AI tools were used to provide feedback on the beforementioned aspects. All generated content was reviewed critically, verified and revised by the authors.