# Chronic Physical Climate Risk and Corporate Financial Policies *

Rong Geng† Mahdieh Vosough Gohari ‡

December 17, 2025

**Abstract**

In this paper, we use temperature and precipitation data to develop a new objective measure for firms' exposure to chronic physical climate risk, weather change. We examine how this exposure is related to firms' financing and cash policy. Our findings confirm a positive association between weather induced cash flow volatility and firm valuation, Q-ratio. We document that firms with higher weather risk have less long-term debt with a larger share of short-term debt. These firms pay higher cost of debt for their loans which indicates lenders' reaction to weather risk. Furthermore, they have higher short-term debt volatility and hold more cash which are different channels to manage their liquidity risk as a result of their weather induced cash flow risk. Our work contributes to the existing literature in measuring chronic physical climate risk for firms and the association between this risk with corporate financial policies.

**JEL Classification:** Climate Risk, Weather Anomalies, Corporate Decisions, Sustainability

*We are grateful to the discussants and participants at the International Conference on Sustainability, Environment, and Social Transition in Economics and Finance (SESTEF) Paris 2024, the Conference on Sustainable Banking and Finance (CSBF) Naples 2025, and the 2025 PhD Nordic Finance Network workshop at Copenhagen Business School for valuable comments and discussions. We also thank Bruno Gerard, Ilan Cooper, Adam Walter Winegar, Leon Bogdan Stacescu, and Costas Xiouros at BI Norwegian Business School for their helpful suggestions and feedback.

†Department of Finance, BI Norwegian Business School, rong.geng@bi.no

‡Department of Finance, BI Norwegian Business School, mahdieh.v.gohari@bi.no

# 1. Introduction

In January 2025, the World Meteorological Organization (WMO) announced year 2024 as the warmest year on record with reporting the last ten years as the ten warmest years[1]. Recent weather changes reflect not only the natural weather variations but also are a result of the human caused climate change. With the climate change crisis going forward these changes are expected to persist and worsen (IPCC (2022)). Therefore, they are likely to affect and reshape economies in a larger extent, affect businesses in different sectors and cause consequent financial policy adaptations. In this paper we estimate the magnitude of firms' cash flow risk induced by weather change using a new objective measure; and study how this risk is associated with firms financial decisions and valuation.

The economic and financial losses driven by physical climate risk and the climate related hazards belong to two main categories: acute physical climate risk and chronic physical climate risk. Acute climate risk is related to what we know as natural disasters: events that arise from extreme climate events such as hurricanes, floods, droughts, etc. Chronic climate risk arises from progressive changes in climate patterns such as temperature rise, changes in precipitation or sea-level rise (Campiglio et al. (2022)). The existing literature largely focuses on the acute climate hazards' impact on various economic and financial variables. Furthermore, the economics literature studies the effect of weather or temperature on economic performance of countries and financial stability (Gallup et al. (1999), Nordhaus (2006), Bansal and Ochoa (2011), Dell et al. (2009)). Yet, while acute climate risks have been extensively studied, the chronic dimension of physical climate risk remains largely overlooked in finance research, leaving a gap in the measurement and understanding of how firms assess and respond to weather anomalies.

In this paper we fill this gap by quantifying chronic physical climate risk exposure for firms. We use temperature and precipitation values from the National Oceanic and Atmospheric Administration (NOAA) as our weather variables. We believe this approach provides clarity and comprehensiveness for the foundation of our weather exposure measure construction. Using a z-score methodology we measure weather change compared to historical weather at the US county and national levels. We use a panel regression to estimate firms' cash flow exposure to weather anomalies, in a similar fashion as Pérez-González and Yun (2013). We then examine the association between weather exposure and firms corporate financial policies. To our knowledge, our paper is the first to construct a comprehensive weather exposure measure in firm-level across sectors and industries and to study the association between this exposure and firm corporate decisions.

[1] https://wmo.int/news/media-centre/wmo-confirms-2024-warmest-year-record-about-155degc-above-pre-industrial-level.

To review the current finance literature within physical climate risk we categorize papers in three groups. First, are papers with a **comprehensive climate risk** measurement including Ginglinger and Moreau (2019) where they use Climate Risk Impact Screening (CRIS) measure, Sautner et al. (2023a) which use earnings call transcripts textual analysis to construct different measures of climate risk including physical climate risk exposure, and Li et al. (2024) which also use earnings call transcript to compute both chronic and acute physical climate risk as well as transition risk. Second, are the existing studies which use or construct a measure of **acute physical climate risk**, natural disasters; studies relevant to our research question in context of acute climate risk are Huang et al. (2018) and Elnahas et al. (2018), among others. Third, are the existing papers on **chronic physical climate risk** measurement or analysis including Pankratz et al. (2022), Kirk et al. (2022), Pérez-González and Yun (2013), and Hugon and Law (2019) which use temperature as a weather measure and Brown et al. (2021) which use snow-depth as their weather variable. To our knowledge, Zhang (2022) is the only paper which uses both temperature and precipitation at the state and national levels in the US. These papers use different approaches to measuring weather anomalies, weather exposure, and firms' performance sensitivity to weather changes. Kirk et al. (2022) and Pérez-González and Yun (2013) use a weather induced volatility method to find firms performance exposure to weather anomalies. Zhang (2022) uses a difference in R-squared methodology to compute firm performance sensitivity to weather anomalies, how much of firms performance is explained by weather change. Other studies use the weather variable (temperature or snow-dept) directly or as the number of days with high temperature in relation with other variables (including financial variables).

Investors are concerned with factors that expose firms' cash flows and operations to fluctuations and uncertainty. Weather change may represent an important source of such risk. Accordingly, we develop and analyze a measure of firms' exposure to weather risk, which is the central construct of the paper. The existing literature neither provides a comprehensive measure of weather exposure nor examines its relationship with corporate decisions in depth. We fill this gap by constructing a more complete measure of weather exposure and analyzing its association with firms' valuation, financing, and cash policies.

To construct a measure of weather change, we first obtain temperature and precipitation data in monthly frequency from the National Oceanic and Atmospheric Administration (NOAA) for the period 1895 to 2024. To have the same frequency between weather data and firm's fundamentals we compute quarterly temperature and precipitation values as the average of the monthly measures. We take two steps to compute cash flow weather exposure. In the first step, we find the temperature and precipitation changes compared to the historical record at both the local, the county where firm headquarter is located, and the national, across all US counties, levels. To assess this change we use

a z-score methodology. We compute the quarterly temperature (precipitation) z-score as the difference between each quarter's temperature (precipitation) and the average temperature (precipitation) of the same quarter in the previous years divided by the standard deviation of the same quarter's temperature (precipitation) in the historical record. For county level measures we use the same county's historical weather data for each quarter. For national measures we take the average of quarterly county level z-scores.

In the second step, we estimate weather exposure for a sample of firms which are headquartered in the US. We obtain historical headquarter data for our sample from 10-K filling. Our sample includes 420,107 observations for 5,692 unique firms for the period 1993 to 2023. Next, we estimate weather $\beta$s by regressing firm cash flow on our four weather measures, local and national average temperature and local and national average precipitation measures. Using the firm-level $\beta$s we compute the weather induced volatility for each firm and quarter[2]. Our method is inspired by Brown et al. (2021) which estimates firms' cash flow sensitivity to abnormal winter weather[3], and Pérez-González and Yun (2013) who first computed a performance/operation-weather measure by calculating weather induced volatility. We use the Fama-French 48 industries as our industry classification. For each of the 48 industries and for a rolling window of 36 quarters, we run a panel data regression to measure firm-level $\beta$s using firm specific dummy variables. We further find local, national, and aggregate weather induced volatility (weather exposure) measures using the $\beta$s and weather z-scores.

We use our weather exposure measures to study the association between weather risk and firm corporate decisions and market valuation. Our final sample consists of 248,049 quarters observations for 5,608 unique firms over Q1 of 2002 to Q4 of 2023 period. We use a panel regression where the dependent variable is a financial measure and independent variables include a weather exposure measure, a group of controls, and year and industry fixed effects. Our standard errors are clustered at the firm level. We study three groups of financial variables in this regression: valuation, financing policy, and cash policy variables. For financing policy we include total liability, short-term debt, long-term debt, short-term debt volatility, short-term to long-debt ratio, and cost of debt. Our variables for cash policy include dividend ratio and cash holding.

Our results support the hypothesis that weather risk exposure affects firm valuation and financial policies. We find positive association between valuation (Q-ratio), and weather induced cash flow volatility (WIV). We show that firms with higher WIV tend to have less lower long-term debt and higher short-term debt. Moreover, we find a positive

[2]Weather induced volatility is the standard deviation of the $\hat{Y}$ which is the cash flow weather component that we compute using the estimated $\beta$s.

[3]They explain that weather change might affect cash flow of firms ongoing projects, therefore, they are an important component to be studied in relation with weather.

relation between WIV and short-term to long-debt ratio and short-term debt volatility. This suggests that short-term debt may be a source of cash in times of high cash flow fluctuations (weather induced cash flow volatility). For cash policy measures we find that firms with higher WIV hold more cash, confirming our hypotheses for more conservative cash policy in presence of liquidity risk from weather exposure. All our coefficients are significant in 1% level.

The remainder of the paper is organized as follows. Section 2 describes the background and our hypotheses. Section 3 describes our data and variable construction. In section 4 we explain our sample and descriptive statistics. Section 5 covers the empirical framework and methodology of our study. In section 6 we present our results and in section 7 we present our robustness tests and results. Finally, section 8 concludes.

## 2. Background and Hypothesis

The existing finance literature studying the impact of chronic physical climate risk on firms is limited. Pérez-González and Yun (2013) investigate the use of weather derivatives by the utilities industry and is one of the early works that measures firm-level weather exposure in terms of firm's revenue sensitivity to temperature based measures, CDD and HDD[4]. They use temperature data from the National Oceanic and Atmospheric Administration (NOAA) and find a negative association between weather exposure and revenue, market to book ratio and net debt. Additionally, they show that firms with higher weather exposure use more weather derivatives. They construct a weather induced volatility measure which is the product of the absolute value of weather $\beta$ and standard deviation of weather which is a more precise method than using the temperature value directly[5]. Their weather exposure methodology was adopted in later works including Kirk et al. (2022) where they use temperature from the NOAA and develop a weather impact measure similar to Pérez-González and Yun (2013). Kirk et al. (2022) show there is a positive relation between historical temperature and sales; furthermore, they show future weather can be used for predicting future performance of firms and the predictable effect of weather is not incorporated in analysts forecasts.

Zhang (2022) uses a R-squared methodology and computes firm level revenue weather sensitivity which he refers to as operating weather exposure. He uses both state and national level SPI[6] and minimum and maximum temperature values as weather variables. He constructs a comprehensive weather measure using both precipitation and

[4]Cooling Degree Days and Heating Degree Days

[5]They calculate $\beta$ from $revasets_{it} = \alpha_i + \beta_i \times DD_{it} + \lambda_i * ln(assets_{it}) + \epsilon_t$ regression where $DD_{it}$ is the relevant degree days measure at firm level. They further construct their weather induced volatility measure as $\left|\beta_i^{DD}\right| \times \sigma_i^{DD}$.

[6]Standardized Precipitation Index

temperature at both state and national levels. His weather sensitivity measure captures the difference in R-squared of a baseline model and the same baseline model with added weather variables as regressor. He finds that firms with higher operating weather exposure show less earnings seasonality and higher short-term earnings persistence. In another study, Ginglinger and Moreau (2019) use the CRIS[7] measure of climate risk and estimate its relation with firms' leverage for the period 2010-2018. They find that firms with a high CRIS risk rating have a lower leverage ratio in the post 2015, Paris Agreement period.

In a paper focused on cash flow shocks and credit lines, Brown et al. (2021) use severe weather as a source of exogenous shock. They measure the relation between cash flow and county level abnormal snow for a sample of US firms. They find that abnormal snow affects cash flow negatively causing a weather-induced cash flow shock. They further study how firms manage the consequent liquidity shock and find credit lines as the primary tool for liquidity management. They show that firms facing this weather-induced cash flow shock expand their credit line by more than 50 percent, with short-maturity loans at higher interest. They investigate whether firms use other channels of liquidity management including cash reserves; their results do not provide significant evidence for cash reserves as a primary source of cash flow shock management.

Several recent works assess climate risk using other sources of data than weather measures. Among others, are Sautner et al. (2023a), Sautner et al. (2023b), and Li et al. (2024) use earnings call transcripts analysis to measure different aspects of climate risk. Li et al. (2024) use a sample of U.S. public firms and quantify firms' climate risk exposure by using textual analysis of the earnings call transcripts of US public companies. Their climate risk measure includes both physical and transition risks. They find that transition risk is priced in equity markets, with firms that do not proactively manage transition risk having lower market valuations (Tobin's q). Furthermore, they document that the proactive management of transition risk is associated with increased CapEX investments, innovation (particularly in green patents), and stable employment.

Sautner et al. (2023a) use firms' earnings call transcripts for a large global sample of 10,673 firms headquartered in 34 countries and adapts a machine learning keyword discovery algorithm to estimate a firm-level climate change exposure by capturing analysts and management attention to various climate factors (phrases). They document that this measure of climate risk is associated with green-tech jobs creation and green patenting, and market risk. Particularly, they find that firms with higher overall climate exposure, experience higher premiums in the tail regions of their options prices, reflecting investor willingness to hedge extreme climate risks or bet on climate outcomes. Additionally, they

[7]Climate Risk Impact Screening. CRIS is an aggregate physical climate risk measure developed by Carbon4. Source: https://www.carbon4finance.com/product/physical-risks.

show that firms with higher betas to a climate change exposure factor tend to experience higher uncertainty, which is reflected in higher returns, indicating that markets price in the uncertainty related to future climate developments. In a later paper, Sautner et al. (2023b) draw on their previous work and study how financial markets price firm-level exposure to climate risk. Using a sample of S&P 500 firms between 2002 and 2020, they find that, on average, the realized risk premium for climate change exposure is zero, but investors expect a modest positive risk premium for stocks with higher exposure, particularly due to the opportunities arising from the low-carbon transition. The risk premium fluctuates over time, reflecting investor perceptions of climate-related opportunities and risks, with a sharp decline during the 2008 financial crisis followed by an upward trend. The authors identify several factors influencing the risk premium, including advancements in green technologies, the adoption of state-level climate adaptation plans, and flows into ESG funds, suggesting that the risk premium evolves dynamically as these factors change.

Among other recent papers in this strand of literature is Huij et al. (2023) which introduces a forward-looking indicator of climate transition risk, "Carbon Beta". They find that high carbon beta assets under-perform during periods of heightened climate concern, such as during extreme weather events, abnormally high temperature or drought event, or when climate policy uncertainty increases. They also find a negative association between carbon beta and green innovation, suggesting that firms with lower exposure to climate risk tend to be more innovative in green technologies. They further show that carbon beta can be used to hedge climate risks in investment portfolios, with assets with negative carbon betas providing a climate hedge. Acharya et al. (2022) use two measures of heat stress including Spatial Empirical Adaptive Global-to-Local Assessment System (SEAGLAS) and Moody's 427 measures of climate stress exposure and study the impact of heat stress on asset prices. They find that local exposure to heat stress is associated with higher municipal and corporate bonds yield spreads and higher expected return for firms' stocks in equity markets.

In our study we use weather measures including average temperature and precipitation to estimate our weather exposure in firm-level. We follow Pérez-González and Yun (2013) work and calculate weather induced volatility of cash flow for firms. Our measure includes both temperature and precipitation weather variables for both local (county) and aggregate (national US) levels. We further study a comprehensive set of variables in relation to our weather exposure measure which we explain together with related hypothesis in the following.

### 2.1. Choice of Variables

To choose our set of variables we have focused on our primary research question: "How is chronic physical climate risk associated with firms financial policies and valuation?". The variables represent a broad set of measures for firms financial policies and valuation. Our set of variables include: Q-ratio for valuation; total liability, long-term debt, short-term debt, short-term debt ratio, short-term debt volatility, and cost of debt, for financing policies; and dividend ratio and cash holding for cash policies, for variable definition see table I. The variables, their categories, the related existing literature, and our hypothesis regarding each variable are presented in details below:

### 2.2. Weather Exposure and Financing Policy

Firms need to build organizational resilience and adaptation plans to deal with climate risk and extreme weather events (Linnenluecke and Griffiths (2010)). In the acute climate risk literature, Huang et al. (2018) find that firms located in countries characterized by more extreme weather are likely to hold more cash, use less short-term debt, more long-term debt, and to be less likely to distribute cash dividends. In another study, Elnahas et al. (2018) show that firms headquartered in areas with more probability of natural disaster seek higher financial flexibility and have more prudent leverage policies. Ginglinger and Moreau (2019) find similar results: forward-looking physical climate risk leads to lower leverage ratios in the post-2015 period. Dessaint and Matray (2017) study managers' reaction to hurricane events and find that after hurricane occurrence in firms' neighboring areas, managers increase their cash holdings temporarily.

In a recent paper, Brown et al. (2021) study weather-induced cash flow shock's relation with credit lines. They show firms rely mainly on credit lines when managing their liquidity after a cash flow shock[8]. They find that firms facing cash flow shocks have a large increase in their credit line, more than 50 percent, meaning they acquire extra credit to maintain sufficient liquidity; the new credit lines include loans with shorter maturity and higher interest rates. They also show increasing cash holdings is not a primary method to manage liquidity risk.

Since the literature on weather exposure and corporate policy is limited and the existing results are more focused on weather extremes and natural disaster, it is particularly important to consider the difference between the nature of acute and chronic climate events when relating them to firms. We discuss this in the following subsections.

[8]They use severe winter weather as the exogenous cash flow shock. They use snow fall data from NOAA in county level.

### 2.2.1. Weather Exposure and Debt Financing

We investigate the association between firms' weather exposure and their financing policy; in particular, their use of debt financing , the share of long-term and short-term debt, and the volatility of the share of the short-term debt. Brown et al. (2021) document a positive relation between weather-induced liquidity shock and credit lines with short maturity. They find that firms facing cash flow shock increase their credit lines and use short-term debt with higher interest as an effective strategy to manage their liquidity risk.

In addition, we show that a share of cash flow volatility is weather induced. Therefore, we refer to the existing literature which estimates cash flow volatility (CFV) association with capital structure. Keefe and Yaghoubi (2016) develop a comprehensive set of (CFV) measures and study the relation between firms cash flow volatility with debt and debt maturity. They use a large sample of US Corporations for the period 1974 to 2012 and find that firms with higher cash flow volatility use less debt and reduce their long-term debt the most while the probability of holding short-term debt increases with CFV for these firms.

One argument for short-term debt increase in times of liquidity risk is that firms need to compensate the cash flow fluctuations with some other sources of cash; one source is short-term debt financing. Using short-term debt financing is considered as a dynamic resilience strategy here, to help firms to recover from transitory weather change effects (Rose (2004)). One way to test this is to assess the short-term debt volatility in relation with weather exposure; and a positive relation between the two would support the view that firms use short-term debt financing as a resilience strategy and not as a main financing policy component.

In light of the existing evidence, we expect to find that firms with high weather exposure have less total liability, less long-term debt, more short-term debt, and higher short-term debt volatility in our results. We also measure the ratio of short-term debt to total liability which we expect to be positively associated with weather exposure.

### 2.2.2. Weather Exposure and Cost of Debt

Kling et al. (2021) study the effect of climate vulnerability on firms cost of capital. They find a high direct and indirect increase in the cost of debt for more vulnerable firms. They do not find a strong association between climate-vulnerability and cost of equity. In another study, Chava (2014) documents that firms with more environmental concerns[9] have significantly higher cost of capital for both equity and debt financing. Brown et al. (2021) finds that firms with weather-induced cash flow shock receive less favorable credit

[9]The environmental concern data is obtained from KLD.

terms with higher cost of loan. Ginglinger and Moreau (2019) find that firms with higher climate risk[10] have higher cost of debt. In our analysis, we expect to find higher cost of debt for firms with higher weather exposure. We believe the higher cost of debt is the lender's reaction to the borrower's weather-induced liquidity risk.

### 2.3. Weather Exposure and Cash Policy

Two other sources, discussed in the literature, for weather-induced liquidity risk management are cash dividend reductions and cash holding increases. Huang et al. (2018) and Dessaint and Matray (2017) study firms' cash dividend and cash holding policy responses to natural disaster events. In the weather anomalies relevant literature, Pérez-González and Yun (2013) find that, for firms in utilities industry, higher exposure is associated with lower dividends, and Huang et al. (2018) find firms in countries with a higher Global Climate Risk Index have higher cash holding and pay less cash dividend. However, Brown et al. (2021) do not find cash reserve as a primary source for liquidity management after a weather-induced cash flow shock. We expect to observe lower dividend ratio for firms with higher weather exposure; to check for cash reserves we look into firm cash holding measure. We expect to find a positive relation between cash holding and weather exposure.

### 2.4. Weather Exposure and Valuation

We use the Q-ratio to investigate the relation between firms' weather exposure and their valuation. The Q-ratio reflects the overall consensus of investors about the market valuation of firms. Because weather exposure is linked with cash flow volatility, we connect our hypothesis to the literature on cash flow volatility and valuation. The results in this strand of literature are mixed. Rountree et al. (2008) analyze a large sample of 4000 unique firms over 16 years and find that cash flow volatility, as a measure of standard deviation of operating cash flow, is negatively and significantly associated with Q-ratio. They control for several measures of risk including systematic risk and idiosyncratic risk, and other financial variables that are related to value such as size, profitability, growth, leverage, and industry affiliation.

In a later study, Chi and Su (2017) find an opposite relation between cash flow volatility and firm valuation. They measure cash flow volatility as the standard deviation of quarterly cash flow over book assets for the last 20 quarters and valuation is measures by Q-ratio. They develop a model to illustrate the dynamics between cash flow volatility and firms valuation. Their theoretical framework explains a positive association between the two variables for a large set of firms. Their empirical analysis which supports their

[10]The climate risk is measured by CRIS, Climate Risk Impact Screening, which is an aggregate physical climate risk measure.

theoretical findings. They further argue that in previous works as Rountree et al. (2008) cash flow volatility is measured without standardizing per share size across firms which leads to a biased estimation of the cash flow volatility and Q-ratio association results.

In our study, we measure cash flow volatility as in Chi and Su (2017). We argue that as weather induced volatility is a part of cash flow volatility, therefore, it follows the same association with valuation as cash flow volatility. Thus, we expect to find a positive and significant relation between weather exposure, weather induced volatility, and valuation, Q-ratio.

# 3. Data and Variable construction

## 3.1. Data

We obtain **weather data** on temperature and precipitation from the National Oceanic and Atmospheric Administration (NOAA). NOAA collects and provides data on a large range of weather variables. The data is collected from weather stations across the US and is presented at different frequencies from which the most granular is daily. In our study, we use monthly average temperature and precipitation data at the county and national levels. The weather data is historical and goes back to 1895.

**Financial and fundamentals data** is obtained from Compustat quarterly database. In order to match county weather data with historical firm headquarter data, we download **historical headquarter information** reported in SEC 10-K fillings from the University of Notre Dame website [11]. The 10-K fillings data contains historical records of firm headquarter location from 1993 to 2023 from which we extract the 5-digit FIPS code corresponding to the firm headquarter county. For firms with missing FIPS codes, we populate the missing values with the most recent available FIPS code from the firm's historical data. This ensures continuity and minimizes data gaps while maintaining accuracy and consistency in our sample.

## 3.2. Variable Construction

### 3.2.1. Weather Change Measure

We obtain our weather data form the NOAA for precipitation and temperature in monthly frequency. To have the same frequency between weather and financial data, we take the average of monthly values for each quarter and calculate the county level and national level quarterly average temperature and precipitation. Referring to the definition of chronic physical climate risk, we are interested in the average temperature

[11] https://sraf.nd.edu/sec-edgar-data/10-x-header-data/.

and precipitation changes at the county and national level. To measure these changes, we use a z-score methodology and compare the average temperature and average precipitation of a quarter with the same quarter's measures over the historical record. In this fashion we observe how temperature and precipitation have risen or fallen compared to the long-term average temperature and precipitation in the same county. The following equations formulate the local and national z-scores for temperature and precipitation:

$$Z_{q,i,T}^{Local,Temp} = \frac{Temp_{q,i,T} - Mean_{q,i,Hist}^{Temp}}{Sd_{q,i,Hist}^{Temp}} \tag{1}$$

$$Z_{q,i,T}^{Local,Prec} = \frac{Prec_{q,i,T} - Mean_{q,i,Hist}^{Prec}}{Sd_{q,i,Hist}^{Prec}} \tag{2}$$

The $Z_{q,i,T}^{Local,Temp}$ compares the average temperature of quarter $q$ for **county** $i$ at year $T$ with quarter $q$'s average temperature over the full previous historical period. The $Z_{q,i,T}^{Local,Prec}$ value measures how much the average precipitation of quarter $q$ for **county** $i$ at year $T$ differs from the quarter $q$'s historical average precipitation. $Temp_{q,i,T}$ and $Prec_{q,i,T}$ are quarter $q$'s average temperature and precipitation for county $i$ at year $T$, respectively. The greater the z-scores' values deviation from 0, the more extreme is the weather change compared to the historical record. The $Mean_{q,i,Hist}^{Temp}$ and $Mean_{q,i,Hist}^{Prec}$ are the average temperature and precipitation values for quarter $q$ and county $i$ over the previous historical period. The $Sd_{q,i,Hist}^{Temp}$ and $Sd_{q,i,Hist}^{Prec}$ are the standard deviation of average temperature and precipitation values for quarter $q$ and county $i$ in the past years, respectively. If we are calculating $Z_{q,i,T}^{Local,Temp}$ for year $T$ the historical mean and standard deviation are calculated for all past years in the historical record up to year $T-1$[12]. We compute national average temperature and precipitation changes in the same fashion:

$$Z_{q,T}^{Nat,Temp} = \frac{Temp_{q,T} - Mean_{q,Hist}^{Temp}}{Sd_{q,Hist}^{Temp}} \tag{3}$$

$$Z_{q,T}^{Nat,Prec} = \frac{Prec_{q,T} - Mean_{q,Hist}^{Prec}}{Sd_{q,Hist}^{Prec}} \tag{4}$$

Where $Z_{q,T}^{Nat,Temp}$ and $Z_{q,T}^{Nat,Prec}$ are the national temperature and precipitation changes for quarter $q$ and year $T$. Similar to the local Z-score measures, $Temp$ and $Perc$ refer to temperature and precipitation which have national aggregation level in national

[12]For example $Z_{1,i,2002}^{Local,TempQ} = \frac{Temp_{1,i,2002} - Mean_{1,i,Hist}^{Temp}}{Sd_{1,i,Hist}^{Temp}}$ finds the z-score for county $i$ for quarter 1 of year 2002 by dividing the difference between the temperature of the first quarter of 2002 and the mean value of all quarter 1 temperature values before and including year 2001, by the standard deviation value of all quarter 1 temperature values before and including year 2001.

Z-score equations; $Mean$ and $Sd$ are also the mean average and standard deviation of the national variables for quarter $q$ of all previous years. In the following parts of the paper, for simplicity, we refer to time as $t$ which is a quarter-year variable.

### 3.3. Firm Level Weather Exposure

Among the papers which use performance or operation weather exposure/sensitivity two methodologies are dominant: estimating a weather induced volatility measure or using difference in R-squared of two sets of time-series analysis to measure how much of the performance/operation is explained by weather changes. Pérez-González and Yun (2013) and Kirk et al. (2022) are examples of studies using the weather induced volatility methodology and Zhang (2022) is the only paper we found which uses the difference in R-squared methodology.

Although the R-squared methodology is intuitive in a way that it explains how much of the performance/operation change is explained by weather anomalies, it lacks the power to demonstrate whether this portion exposes any risk to investors. Intuitively, it might be the case that a firm has a moderate or high percentage of its performance explained by weather change while it is not material for investors and does not present a weather risk exposure to firms' investors or other stakeholders. Therefore, it is not a concern for capital markets and firms and does not need further attention. The weather induced volatility measure on the other hand is the product of the regression coefficient of weather on performance multiplied by the weather standard deviation, Pérez-González and Yun (2013), which in a simplified form is the following formulation:

$$CashFlow_{j,T} = \alpha_{j,T} + \beta \times Weather_{j,T} + \epsilon_{j,T} \tag{5}$$

$$WIV = |\beta| \times \sigma_{Weather} \tag{6}$$

Where $WIV$ stands for Weather Induced Volatility which entails $\beta$ and measures the correlation between performance and weather. Therefore, it estimates the firm performance exposure to weather anomalies. We use the weather induced volatility concept in our study, however, with a **different formulation**, explained below.

#### 3.3.1. Cash Flow Weather Exposure

Weather change can affect the cash flow of the ongoing projects of firms (Brown et al. (2021)). Therefore, we are interested in measuring firms' cash flow exposure to weather: henceforth, weather exposure for simplicity.

To estimate the weather exposure we use a panel regression methodology. First,

within each window of 36-quarters and for each county, we orthogonalize the local weather with respect to the national weather by regressing local weather $Z-Scores$ on national weather $Z-Scores$, equation (7). In this way, the orthogonal component of local weather is uncorrelated with the national weather.

$$\begin{aligned} Z_{k,t}^{Local,temp} &= \alpha_{k,t}^{temp} + \beta Z_t^{Nat,temp} + \epsilon_{k,t}^{temp} \\ Z_{k,t}^{Local,prec} &= \alpha_{k,t}^{prec} + \beta Z_t^{Nat,prec} + \epsilon_{k,t}^{prec} \end{aligned} \tag{7}$$

Where $Z_{k,t}^{Local,temp}/Z_{k,t}^{Local,prec}$ is the Z-score for county $k$ at time, quarter-year, $t$ for temperature/precipitation and $Z_t^{Nat,temp}/Z_t^{Nat,prec}$ is the national Z-score, across all counties, at time $t$ for temperature/precipitation. The variables of interest are the intercepts and the residuals, $\alpha_{k,t}^{temp}$, $\alpha_{k,t}^{prec}$, $\epsilon_{k,t}^{temp}$, and $\epsilon_{k,t}^{prec}$. The isolated local weather change, $IZ$ is therefore, the sum of intercept and residual for each county.

$$\begin{aligned} IZ_{k,t}^{Local,temp} &= \alpha_{k,t}^{temp} + \epsilon_{k,t}^{temp} \\ IZ_{k,t}^{Local,prec} &= \alpha_{k,t}^{prec} + \epsilon_{k,t}^{prec} \end{aligned} \tag{8}$$

In the next step, we compute weather betas. To estimate betas we use a rolling window (estimation period) of 36 quarters. We use the Fama-French industry classification, which consists of 48 industries in our sample, and run the following regressions over a rolling window of 36 quarters within each industry[13].

$$\begin{aligned} CF_{i,t} = \beta_{1,i} D_i Weather_t^{Local,temp} + \beta_{2,i} D_i Weather_t^{Nat,temp} + \beta_{3,i} D_i Weather_t^{Local,prec} + \\ \beta_{4,i} D_i Weather_t^{Nat,prec} + \beta_5 Ln(assets)_{i,t} + \beta_6 BM_{i,t} + \beta_7 Total\ liability_{i,t} + fe_i + \sigma_{i,t} \end{aligned} \tag{9}$$

Where $CF_{i,t}$ is the cash flow for firm $i$ at time $t$ and $D_i$ is firm dummy which takes the value of 1 for firm $i$. $Weather_{temp}^{local}$ is the local average temperature change measure which is equal to $IZ_{k,t}^{Local,temp}$, equation (8), and $Weather_{temp}^{Nat}$ is the national temperature change, $Z_t^{Nat,Temp}$, at time $t$. For precipitation, $Weather_{prec}^{local}$ is equal to $IZ_{k,t}^{Local,prec}$ which is the local average precipitation change measure, from equation (8), and $Weather_{prec}^{Nat}$ is the national precipitation change, $Z_t^{Nat,prec}$, at time $t$. We add three firm controls to the equation which are $Ln(assets)_{i,t}$, $BM_{i,t}$, and $Total\ liability_{i,t}$ which are is the natural logarithm of assets, book to market ratio, and leverage ratio for firm $i$ at time $t$. $fe_i$ is the firm fixed effects. Time variable $t$ is a quarter-year variable.

[13]For example, for firms within the Food Products industry we use the available values from quarter 1 of year N to quarter 4 of year N+9, 36 quarters window, to estimate firm-level betas for all four weather variables. The next rolling window is from quarter 2 of year N to quarter 1 of year N+10 and so on. For each rolling window the estimated betas are attributed to the last quarter of the rolling window, quarter 36.

Within each rolling window a set of four weather cash flow sensitivity coefficients ($weather\beta$s) are reported at the firm-level. The control variables coefficients are estimated at the industry level.

### 3.3.2. Cash Flow Weather-Induced Volatility

In the next step, we calculate the weather-induced cash flow volatility (WIV) for local, national, and aggregate weather exposures for each firm and quarter in our sample. WIV is estimated using the same 36-quarter rolling windows as in the beta estimation. To compute WIV, we **first** calculate $\hat{Y}_{i,t}$, the cash flow weather component, separately for local, national, and aggregate weather measures within each rolling window. For each window, $\hat{Y}_{i,t}$ is obtained using the following equations:

$$\begin{aligned} \hat{Y}_{i,t}^{Local} &= \hat{\beta}_{1,i} Weather_t^{Local,temp} + \hat{\beta}_{3,i} Weather_t^{Local,perc} \\ \hat{Y}_{i,t}^{Nat} &= \hat{\beta}_{2,i} Weather_t^{Nat,temp} + \hat{\beta}_{4,i} Weather_t^{Nat,perc} \end{aligned} \tag{10}$$

The aggregate weather effect is then obtained as the sum of local and national components:

$$\hat{Y}_{i,t}^{Agg} = \hat{Y}_{i,t}^{Local} + \hat{Y}_{i,t}^{Nat} \tag{11}$$

Here $\hat{\beta}_{1,i}$, $\hat{\beta}_{2,i}$, $\hat{\beta}_{3,i}$, and $\hat{\beta}_{4,i}$ are the estimated exposure of firm $i$ to local and national temperature, equation (9), computed within each 36-quarter rolling window. $\hat{Y}_{i,t}^{Local}$ and $\hat{Y}_{i,t}^{Nat}$ are the cash flow weather components calculated for firm $i$ and for every quarter within each rolling window. **Second**, Once $\hat{Y}_{i,t}$ is computed, we calculate its standard deviation within the rolling window, which serves as our **weather induced cash flow volatility (WIV)** measure[14].

$$WIV_i^{Local} = sd(\hat{Y}_{i,t}^{Local}), \quad WIV_i^{Nat} = sd(\hat{Y}_{i,t}^{Nat}), \quad WIV_i^{Agg} = sd(\hat{Y}_{i,t}^{Agg}) \tag{12}$$

$$ratio_i = WIV_i / Sd(CF_i) \tag{13}$$

To ensure the plausibility of the measure, we compute the ratio of weather-induced volatility to total cash flow volatility, $ratio_i$. Occasionally, this ratio exceeds 1, indicating that weather accounts for more than 100% of observed cash flow variability. To address this, we winsorize this ratio at the 0.5% and 99.5% percentiles, constraining all values to lie between 0 and 1. The winsorized ratio is then used to recalculate weather-induced volatility by multiplying the cash flow standard deviation, $Sd(CF_i)$, back in the winsorized $ratio_i$. We use the re-calculated measure in our analysis.

[14]For each rolling window we compute one set of coefficients ($\hat{\beta}_{1,i}$, $\hat{\beta}_{2,i}$, $\hat{\beta}_{3,i}$, and $\hat{\beta}_{4,i}$), 36 $\hat{Y}$s for 36 quarters, and one set of WIVs ($WIV_i^{Local}$, $WIV_i^{Nat}$, and $WIV_i^{Agg}$).

The Weather Induced Volatility is our measure of firms' **Chronic Physical Climate Risk** which we, henceforth, refer to as **weather risk** for simplicity.

# 4. Sample and summary Statistics

## 4.1. Sample

Due to the availability of historical headquarter data from 10-k filling, our initial sample period is from 1993 to 2023. The initial sample includes 779,303 firm-quarter observations (15,681 unique firms) from 1993 to 2023. In order to estimate weather exposure, we restrict our sample to firms with more than 36 quarters of observations in the period between 1993 and 2023. In addition, we only keep firms with no missing values for cash flow and control variables (total assets, book-to-market ratio, and leverage). After applying the filters, our sample for the first stage weather exposure estimation has 420,107 firm-quarter observation with 5,692 unique firms. For each firm-quarter, we use the past 36 quarters rolling window to estimate firm's historical exposure to weather. The detailed method is described in Section 3.1.1. After estimation, our weather risk measures (WIV) are available from 2002 to 2023 for a final sample of 248,049 observations for 5,608 unique firms.

[Insert Table I about here]

[Insert Table II about here]

The summary statistics for our final regression sample and the correlation matrix for our full set of variables are reported in Table I and II. As shown in Table II, the mean of aggregate weather-induced volatility (WIV) is 0.013 and the median is 0.009, indicating that in the full sample, the distribution of aggregate WIV is right skewed and has a long tail for high values. The standard deviation (0.013) suggests moderate variability in the aggregate WIV. For financial variables, the Q-ratio has a mean and standard deviation of 1.515 and 1.455; the large standard deviation reveals large dispersion in growth opportunities in our sample. The average total liability is 0.537 with a median of 0.538 which indicate that firms finance slightly more than half of their assets with liabilities, and that more than half of the sample follow this financing policy. The short-term and long-term debt ratios average 0.039 and 0.182, respectively, which shows that firms on average use more long-term debt. However, the moderate mean of the short-term debt volatility, 0.038, indicates that firms vary in their reliance on short-term funding.

In terms of correlation, the aggregate WIV has a high correlation with cash flow volatility, 0.874, and the local WIV and national WIV are moderately correlated, 0.676. We also observe a negative correlation between aggregate WIV and firm size, -0.455, as

proxied by total assets. This indicates that firms with higher weather risk tend to be smaller compared to those with lower weather risk. Total assets may serve as a proxy for geographic diversification, as larger firms are more likely to operate across multiple regions within the United States. In contrast, smaller firms are often concentrated in a limited number of locations, making them more exposed to the impacts of local weather variations.

### 4.2. National Weather Changes and Trends

In figure 1, we plot the national z-score variations over the sample period for average temperature and precipitation, along with fitted linear trends to illustrate their long-term evolution. Panel (a) shows substantial fluctuations in temperature, with periods of both abnormally high and low values. However, high-temperature deviations occur more frequently, as indicated by several quarters in which the temperature z-score approaches 3. The upward-sloping linear trend further indicates that temperature z-scores have increased over time, reinforcing evidence that the U.S. has become increasingly exposed to warmer weather conditions.

[Insert figure 1 about here]

Panel (b) displays the quarterly national average precipitation z-scores along with the fitted linear trend. The series shows considerable variability, with z-scores occasionally approaching above 2 and below –1.5, reflecting periods of unusually wet or dry conditions. The fitted trend line, which remains close to zero, with a slope of –0.0013, indicates that there is no strong long-term upward or downward trend in national precipitation over this period. However, by following the fluctuations in the z-scores, we can see a nonlinear pattern showing that precipitation initially declines, then rises, and later trends downward again. This suggests that while there is no consistent long-term trend, the data exhibit shorter-term cycles or irregular shifts in national precipitation over the sample period.

## 5. Regression Analysis

We use pooled OLS regression analysis to study weather risk association with different financial variables, in firm-level and quarterly frequency. We study this by measuring how firms' financing policy, cash policy, and valuation are associated with firm's weather risk. We use Q-ratio as our valuation measure; total liability, short-term debt, long-term debt, short-term debt volatility, short-term to long-term debt ratio, and cost of debt as variables for financing policy, and cash dividend and cash holdings as cash policy related variables. We run our regressions in both **uni-variate** and **multi-variate** forms

with the latter having the following equation:

$$\begin{aligned} Y_{i,t} = \delta_1 WIV_{i,t-1} + \delta_2 Ln(assets)_{i,t-1} + \delta_3 ROA_{i,t-1} + \delta_4 BM_{i,t-1} + \delta_5 PPE_{i,t-1} \\ + \delta_6 Investment_{i,t-1} + \delta_7 Leverage_{i,t-1} + Year + Industry + \sigma_{i,t} \end{aligned} \tag{14}$$

This regression formulates the general form of our multi-variate identification where $Y_{i,t}$ can be: Q-ratio, total liability, Short-term debt, Long-term debt, the ratio of short-term debt over long-term debt (debt ratio), Short-term debt volatility, Cost of debt, Dividend ratio, and Cash holding measures for firm $i$ at time $t$. $WIV_{i,t-1}$ is firm $i$'s weather induced volatility estimated using past 36 quarters data before quarter $t$, weather induced volatility measures from equations (9) and (10). Specifically, $Ln(assets)_{i,t-1}$ controls for size, $ROA_{i,t-1}$ captures profitability, $BM_{i,t-1}$ accounts for growth opportunities, $PPE_{i,t}$ controls for asset tangibility, $Investment_{i,t}$ captures prior investment activity, and $Leverage_{i,t-1}$ controls for firm capital structure; all the control variables are associated with firm $i$ and quarter $t-1$. The leverage ratio control is used for cash policy and valuation regressions only. $Year$ is year fixed effects which control for macroeconomic and time-specific shocks common to all firms, and $Industry$ is industry fixed effects which account for sector-specific characteristics that may influence financial policies or investment behavior. Our panel includes firms in 48 Fama-French industry classification for the period 2002 to 2023. For variables definition and formula please check table A.I in the Appendix.

The **uni-variate** specification is particularly important and informative in our study because it focuses solely on the relationship between the weather induced cash flow volatility measures and each dependent variable. By excluding control variables, this approach isolates the direct association of interest and avoids the possibility that additional variables might blur or influence this relationship.

## 6. Results

Our panel regression results are reported in Tables III–VIII. All specifications include year and industry fixed effects, and standard errors are clustered at the firm level. Table III presents the **uni-variate** regressions for Aggregate WIV, Local WIV, and National WIV in Panels (A), (B), and (C), respectively. Across all three sets of weather-induced volatility measures, the signs and significance levels of the coefficients are broadly consistent with our hypotheses regarding financing policy, cash policy, and firm valuation. For simplicity, the terms **weather induced cash flow volatility (WIV)** and **weather risk** are used interchangeably throughout the remainder of the paper.

[Insert Table III about here]

First, for financing policy, our results show that higher weather induced cash flow volatility (WIV) is correlated with lower total liabilities and lower long-term debt, which may reflect firms' tendency to avoid long-term payment commitments when uncertainty is higher. At the same time, we observe a positive and statistically significant association between WIV and short-term debt. Consistent with Brown et al. (2021), this pattern indicates that short-term borrowing appears to function as a liquidity channel during periods of more volatile or reduced cash flow. We further support this interpretation by noting that both short-term debt volatility and the short-term to long-term debt ratio increase with WIV, implying a shift toward shorter-maturity financing. Finally, we find that higher WIV is linked to higher cost of debt, suggesting that lenders incorporate weather-related cash-flow volatility into loan pricing.

For cash policy variables, we find that higher weather induced cash flow volatility is associated with lower cash dividends and higher cash holdings. This pattern suggests that firms experiencing greater weather related liquidity risk tend to hold more cash and pay out less dividend, consistent with behavior aimed at buffering against potential liquidity shortfalls.

We also document a positive and strongly significant association between WIVs and the Q-ratio, supporting our hypothesis that higher (weather induced) cash flow volatility is linked to higher firm valuation, Q-ratio. This relationship implies that firms experiencing greater weather induced cash flow volatility tend to have higher market valuations relative to their replacement costs. Real options theory provides a framework for understanding this result. In environments characterized by high uncertainty, firms possess valuable option-like investment opportunities: they can defer, expand, contract, or abandon projects as new information arrives. The value of this managerial flexibility increases when uncertainty is higher.

Weather cash flow induced volatility (WIV) captures precisely this form of uncertainty. Higher WIV means that future cash flows become more dispersed, increasing the value of having the option to wait before committing to irreversible investments, or the option to scale operations up or down as conditions change. Since Tobin's Q is a forward-looking measure and reflects the market's evaluation of a firm's growth opportunities, higher WIV translates into a higher Q-ratio because investors place greater value on the firm's embedded real options.

In this sense, the Q-ratio results suggest that weather related uncertainty does not simply impose risk; it also enhances the value of firms' flexibility in timing and adjusting investment decisions. The market prices this flexibility positively. Thus, even though weather volatility increases operational uncertainty, it also increases the strategic value

of managerial discretion leading to higher firm valuation, Q-ratio.

For the **multi-variate** tests, we choose lagged values of ln(assets), return-on-assets (ROA), book-to-market ratio, property plant and equipment (PPE), and investment for our regression specifications. For the cash policy and valuation regressions, we additionally include total liability (leverage) as a control. We report the multi-variate regressions results for Aggregate, Local, and National weather induced cash flow volatility (WIV) in tables IV to VIII.

In table IV we present our results for the association between the aggregate weather induced cash flow volatility (combining local and national weather volatility) and our set of firms financing policy variables. Our results support our hypotheses for the majority of the variables significantly. We describe and analyze our results following the categories for financial variables explained in the background and hypothesis section, section 2.

[Insert Table IV about here]

Regarding **financing policy**, our findings confirm that firms with higher exposure to aggregate weather have less long-term debt while they have more debt with short-term maturity, coefficients of -0.447, and 0.297 for long-term debt and short-term debt, respectively; both coefficients are significant in 1% level. We further find that these firms have higher short-term debt volatility, 0.563 coefficient significant in 1% level, which confirms the hypothesis that short-term debt is used as a source of cash when firms face liquidity risk. Besides, we find a positive and significant, 1% level, association between aggregate weather induced cash flow volatility and cost of debt with 0.177 coefficient which verifies our hypothesis that weather vulnerability for firms is related to less favorable debt financing terms concerning cost of debt. Our results related to total liability is insignificant for aggregate WIV. Looking into the economic significance of our results, we see that one standard deviation increase in firms aggregate WIV is followed with 3.19% decrease in long-term debt and 9.9%, 19.26%, and 12.11% increase in short-term debt, short-term debt volatility, and cost of debt, respectively.

These results suggest that firms facing higher aggregate weather induced cash flow volatility are associated with a more conservative and liquidity oriented financing structure. The significant negative association with long-term debt indicates a link whereby weather vulnerable firms tend to use less fixed, inflexible long-term borrowing, possibly because chronic weather risk coincides with more uncertain future cash flows and a reduced capacity to take on long-term obligations. At the same time, the increase in short-term debt and its volatility is associated with greater reliance on short-maturity borrowing as a flexible buffer against liquidity shortages. Short-term debt can be adjusted quickly,

allowing firms to respond more dynamically to revenue disruptions caused by weather shocks; the higher volatility aligns with more frequent refinancing and rollover activity consistent with managing short-run liquidity needs. The positive association between weather risk and the cost of debt further supports this interpretation, as lenders appear to view weather-vulnerable firms as riskier and demand higher compensation, which is consistent with the findings of Brown et al. (2021).

The financing policy variables results for the local and national WIV are presented in tables V and VI. The signs and significance of the results are the same for all variables except total liability where local weather induced cash flow volatility has a positive and significant association with total liability, 0.49 and significant at 1% level. A possible explanation for this association is that local weather induced volatility is more temporary and region based, allowing firms to take on additional borrowing to meet short-term financing needs, as lenders may view this risk as less systemic. In addition, because total liability combines both short-term and long-term components, the relationship may reflect a more complex mix of movements in the two, resulting in an overall positive association under local weather volatility.

[Insert Table V and VI about here]

Regarding the **cash policy** variables, we find that firms with higher aggregate WIV hold more cash, with a coefficient of 1.808 significant at the 1% level. This association suggests that firms facing greater aggregate weather induced cash flow volatility tend to adopt more precautionary cash policies, retaining additional liquidity to prepare for periods of adverse weather related disruptions. Economically, a one standard deviation increase in aggregate weather risk is linked to a 13.28% increase in cash holdings. These results are consistent with the literature, including Pérez-González and Yun (2013) and Huang et al. (2018), which shows that firms exposed to elevated aggregate weather volatility maintain higher cash buffers, especially when external financing may become more difficult or costly. In this context, holding additional cash serves as an internal insurance mechanism against potential liquidity shortages. We confirm the same link for local and national WIVs. However, we do not find any meaningful or significant associations between WIV and the dividend ratio, indicating that dividend reduction does not appear to be a channel through which firms manage liquidity in response to weather induced cash flow volatility.

[Insert Table VII about here]

Lastly, for **valuation**, we find positive and significant associations between Q-ratio and aggregate weather risk, coefficient of 13.906 significance at 1% level. Our result confirms that firms with higher exposure to aggregate weather change have higher valuation in the

market; an increase of one standard deviation in aggregate exposure to weather (local and national) is associated with a 11.93% increase in Q-ratio relative to the sample average[15]. This result is also consistent with Chi and Su (2017) findings related to the link between cash flow volatility and valuation, Q-ratio. We find similar results for local and national WIV.

[Insert Table VIII about here]

One possible explanation is real options theory: higher weather induced cash flow volatility increases uncertainty, which raises the value of firms' flexibility to adjust investment decisions. Since Tobin's Q reflects the market's assessment of growth opportunities, this added flexibility can lead to a higher Q-ratio.

## 7. Robustness Tests

To examine whether the baseline association between weather induced cash flow volatility (WIV) and firms' financial and cash policies is driven disproportionately by firms that have higher WIV, we add a WIV dummy variable, $D_{H,i,t}$, to equation (14) which is equal to 1 when firm $i$'s aggregate weather induced cash flow volatility in quarter $t$ is above the cross sectional median value, and 0 otherwise. We interact this dummy variable with the continuous aggregate weather induced cash flow volatility measure. equation below:

$$Y_{i,t} = \delta_1 WIV_{i,t-1} + \delta_2 D_{H,i,t} \times WIV_{i,t-1} + \delta_3 Ln(assets)_{i,t-1} + \delta_4 ROA_{i,t-1} + \delta_5 BM_{i,t-1} + \delta_6 PPE_{i,t-1} + \delta_7 Investment_{i,t-1} + \delta_8 Leverage_{i,t-1} + Year + Industry + \sigma_{i,t} \tag{15}$$

This specification allows the slope on weather induced cash flow volatility to differ between relatively low and high risk firms and therefore serves as a robustness check against the possibility that our linear baseline regression results are driven only by the upper tail of the weather risk distribution. In this setting, the coefficient on $WIV_{i,t-1}$ captures the marginal effect of weather induced volatility on $Y_{i,t}$ for firms with below median risk $D_{H,i,t}$, while the coefficient on the interaction term $D_{H,i,t} \times WIV_{i,t-1}$ measures the incremental marginal effect for firms with above median WIV. Hence, for high WIV firms the total effect of weather induced cash flow volatility on the outcome variable is estimated by the sum of the two coefficients, $\delta_1$ and $\delta_2$ here.

[15]The economic significance is calculated as Sd(WIV) multiplied by the coefficient from the panel regression and divided by mean of the dependent variable. For Q-ratio: $13.906 * 0.013/1.515 = 11.93\%$.

### 7.1. Results

The results for our robustness tests are presented in table A.II and A.III. Including the interaction between aggregate weather induced cash flow volatility (WIV) and the high WIV dummy reveals clear heterogeneity in how firms adjust their financing and cash policies as well as the changes in their valuation.

[Insert Table A.III about here]

For **total liability**, the baseline coefficient is negative and significant, –1.710 at the 1% level, while the interaction term is significantly positive, 1.802 at the 1% level. This pattern implies that firms with low WIV show a strong negative association between WIV and total liability, but for high WIV firms this relationship is much weaker and effectively offset by the positive interaction. This means that low WIV firms appear to reduce leverage as weather risk increases, but high WIV firms do not show this same pattern, possibly because they are already operating with constrained financial flexibility, rely on short-term liquidity tools instead of total leverage adjustments, or face limited ability to reduce debt further.

The maturity structure results follow a similar pattern: for **short-term debt**, the interaction term is large and positive, turning an insignificant baseline association into a strong positive link for high WIV firms. For **long-term debt**, the baseline association is positive but becomes negative for high WIV firms due to the large negative interaction term. Likewise, the short-term to long-term debt ratio becomes strongly positive for firms above the median WIV level, indicating a pronounced shift towards short maturity borrowing among these firms. **Short-term debt volatility** also increases more strongly for highly weather induced cash flow volatility firms, consistent with more frequent adjustments to short-maturity credit to manage liquidity needs.

For **cost of debt**, the baseline coefficient is positive and significant, and although the interaction term is insignificant, the overall pattern suggests higher borrowing costs for both groups. In **cash policy**, the interaction term for **dividend ratio** is negative and significant while the baseline model has positive and significant coefficient, very close in absolute value to the interaction term results. When the two coefficients are combined, the net effect for high WIV firms is close to zero, indicating no strong or meaningful association between weather exposure and dividend payments for these firms. On the other hand, **cash holdings** show a strong positive baseline association and an additional positive interaction effect, implying that highly WIV firms accumulate substantially larger precautionary cash buffers. For **valuation**, Q-ratio, aggregate WIV remains strongly and positively associated with Q, but the interaction term is negative and insignificant, indicating that the positive association is broadly similar across exposure groups, though

somewhat weaker among highly exposed firms.

Overall, these results show that the associations found in the baseline regressions, lower long-term leverage, greater reliance on short-term and volatile debt, higher borrowing costs, and more conservative liquidity policies, are disproportionately linked to firms in the upper half of the weather induced cash flow volatility distribution.

[Insert Table A.II about here]

The uni-variate regression results are presented in table A.II. These results show associations that point in the same broad direction as the multi-variate results, firms with higher weather induced cash flow volatility tend to display lower long-term debt, higher short-term borrowing, higher short-term debt volatility, higher cash holdings, and higher valuations. These simple models confirm that the core relationships are present even before controlling for firm characteristics. However, the magnitude and statistical significance of several coefficients differ once controls and fixed effects are included. In particular, some variables that appear significant in the uni-variate setting, such as total liability or dividend ratio, become weaker or take the opposite sign in the multi-variate regressions, indicating that part of the simple correlation was tied to firm size, asset structure, and profitability. Overall, the uni-variate results provide an initial, uncluttered view of the raw correlations, while the multi-variate models refine these patterns and reveal that several of the more nuanced financing responses, such as the substitution toward short-term debt, are more precisely detected once firm characteristics and heterogeneity are accounted for.

## 8. Conclusion

In this study, we use temperature and precipitation data from the National Oceanic and Atmospheric Administration (NOAA) at both county and national levels, measuring quarterly changes (z-scores) relative to historical records. We further obtain financial data from Compustat and firm headquarter data from SEC 10-k fillings for a large sample of US headquartered firms. We estimate firm level weather exposure using rolling window panel regressions linking cash flow to local and national weather changes, with controls for size, leverage, and industry effects. We then compute firms' weather induced cash flow volatility (WIV) as the standard deviation of the predicted cash flow component attributable to weather, capturing the extent to which firms' cash flows respond to climate variability. Using our weather induced cash flow volatility measures we study the association between weather risk and firms' valuation, financing policy, and cash policy. Our sample to estimate weather exposure, weather $\beta$s, includes 5,692 unique public firms located in the US for the period 1993 to 2023. Our final sample which includes the result-

ing WIV and we use for panel regression analysis of firms' financial policies, covers 5,608 unique firms for the period 2002 to 2023.

Our results show that firms with high aggregate weather cash flow volatility(WIV) are associated with higher valuation and distinct financing and cash policies. We verify that these firms tend to have lower long-term debt, while we show a positive relation between WIV and short-term debt and short-term debt ratio with a significantly positive short-term debt volatility which means these firms possibly use short-term debt as a liquidity management tool. We further document a positive and significant association between weather induced cash flow volatility and cost of debt which indicates less favorable debt financing terms for exposed firms and that debt lenders are concerned about the weather change risk these firms' cash flows are exposed to. Our results also confirm positive link between WIV and cash holdings as another channel for liquidity management in relation to weather risk exposure.

In our cash flow weather exposure measure, we include all weather z-scores ranging from extreme positive to near extreme negative values. We acknowledge that extreme z-score values, particularly those approaching $\pm 3$, represent possible extreme weather events, which are beyond the scope of chronic physical climate risk, the progressive changes in weather patterns that we study in this paper. Therefore, we plan to implement a classification strategy to separate possible extreme weather events from progressive changes, and to repeat our analysis to examine how the two groups are associated with cash flow volatility and firms' corporate financial policies.

We contribute to the existing literature by measuring firms' cash flow exposure and weather induced cash flow volatility comprehensively using both temperature and precipitation changes, following the definition of chronic climate risk, in both county and national levels. Besides, we contribute to the climate change literature in finance by studying firms' financing policy and cash policy in relation to weather exposure. In addition to finding new evidence related to chronic physical climate risk and corporate financial policies we also confirms several findings in the existing literature including Brown et al. (2021), Huang et al. (2018), Pérez-González and Yun (2013), and Chi and Su (2017).

# REFERENCES


V. V. Acharya, T. Johnson, S. Sundaresan, and T. Tomunen. *Is physical climate risk priced? Evidence from regional variation in exposure to heat stress*. Number w30445. National Bureau of Economic Research Cambridge, MA, USA, 2022.

R. Bansal and M. Ochoa. Temperature, aggregate risk, and expected returns. Technical report, National Bureau of Economic Research, 2011.

J. R. Brown, M. T. Gustafson, and I. T. Ivanov. Weathering cash flow shocks. *The Journal of Finance*, 76(4):1731–1772, 2021.

E. Campiglio, L. Daumas, P. Monnin, and A. von Jagow. Climate-related risks in financial assets. *Journal of Economic Surveys*, 2022.

S. Chava. Environmental externalities and cost of capital. *Management science*, 60(9): 2223–2247, 2014.

J. D. Chi and X. Su. The dynamics of performance volatility and firm valuation. *Journal of Financial and Quantitative Analysis*, 52(1):111–142, 2017.

M. Dell, B. F. Jones, and B. A. Olken. Temperature and income: reconciling new cross-sectional and panel estimates. *American Economic Review*, 99(2):198–204, 2009.

O. Dessaint and A. Matray. Do managers overreact to salient risks? evidence from hurricane strikes. *Journal of Financial Economics*, 126(1):97–121, 2017.

A. Elnahas, D. Kim, and I. Kim. Natural disaster risk and corporate leverage. *Available at SSRN 3123468*, 2018.

J. L. Gallup, J. D. Sachs, and A. D. Mellinger. Geography and economic development. *International regional science review*, 22(2):179–232, 1999.

E. Ginglinger and Q. Moreau. Climate risk and capital structure. *Université Paris-Dauphine Research Paper*, (3327185), 2019.

H. H. Huang, J. Kerstein, and C. Wang. The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5):633–656, 2018.

A. Hugon and K. Law. Impact of climate change on firm earnings: evidence from temperature anomalies. *Available at SSRN 3271386*, 2019.

J. Huij, D. Laurs, P. A. Stork, and R. C. Zwinkels. Carbon beta: a market-based measure of climate transition risk exposure. *Available at SSRN 3957900*, 2023.

IPCC. *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK and New York, NY, USA, 2022.

M. O. Keefe and M. Yaghoubi. The influence of cash flow volatility on capital structure and the use of debt of different maturities. *Journal of Corporate Finance*, 38:18–36, 2016.

M. Kirk, D. Stice, and H. Stice. The real effects of weather on firm performance, analyst forecasts, and stock prices. *Available at SSRN 4007090*, 2022.

G. Kling, U. Volz, V. Murinde, and S. Ayas. The impact of climate vulnerability on firms' cost of capital and access to finance. *World Development*, 137:105131, 2021.

Q. Li, H. Shan, Y. Tang, and V. Yao. Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6):1778–1830, 2024.

M. Linnenluecke and A. Griffiths. Beyond adaptation: resilience for business in light of climate change and weather extremes. *Business & Society*, 49(3):477–511, 2010.

W. D. Nordhaus. Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517, 2006.

N. Pankratz, R. Bauer, and J. Derwall. Climate change, firm performance, and investor surprises. *Available at SSRN 3443146*, 2022.

F. Pérez-González and H. Yun. Risk management and firm value: Evidence from weather derivatives. *The Journal of Finance*, 68(5):2143–2176, 2013.

A. Rose. Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal*, 2004.

B. Rountree, J. P. Weston, and G. Allayannis. Do investors value smooth performance? *Journal of Financial Economics*, 90(3):237–251, 2008.

Z. Sautner, L. Van Lent, G. Vilkov, and R. Zhang. Firm-level climate change exposure. *The Journal of Finance*, 78(3):1449–1498, 2023a.

Z. Sautner, L. Van Lent, G. Vilkov, and R. Zhang. Pricing climate change exposure. *Management Science*, 69(12):7540–7561, 2023b.

L. Zhang. Operating exposure to weather, earnings predictability, and analyst forecast. *Available at SSRN 4030938*, 2022.

## Table I. Summary Statistics

This table presents the summary statistics for our final sample, including both weather induced volatility measures and financial variables. Cash flow weather induced volatility is measured at the local, national, and aggregate levels, as defined in equation (12). The sample covers 248,049 observations for the period Q1 2002 to Q4 2023. The panel is unbalanced, and N is the number of non-missing values for each variable. Cash flow volatility is calculated as the standard deviation of cash flow over the past 36 quarters (a rolling window of 36 quarters). The debt ratio is the fraction of short-term debt over long-term debt. Short-term debt volatility is measured as the standard deviation of short-term debt over the past 36 quarters. For a detailed explanation of variables, see Table A.I in the Appendix.

| Variable | N | Mean | SD | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| **Aggregate weather volatility** | 248,002 | 0.013 | 0.013 | 0.004 | 0.009 | 0.016 |
| **Local weather volatility** | 248,002 | 0.008 | 0.010 | 0.002 | 0.005 | 0.011 |
| **National weather volatility** | 248,002 | 0.009 | 0.011 | 0.003 | 0.006 | 0.012 |
| **Aggregate WIV ratio** | 248,002 | 0.365 | 0.144 | 0.264 | 0.352 | 0.448 |
| **Local WIV ratio** | 248,002 | 0.246 | 0.137 | 0.146 | 0.227 | 0.323 |
| **National WIV ratio** | 248,002 | 0.268 | 0.148 | 0.158 | 0.247 | 0.354 |
| **Q-ratio** | 247,759 | 1.515 | 1.455 | 0.716 | 1.092 | 1.773 |
| **Cash flow volatility** | 248,049 | 0.035 | 0.033 | 0.014 | 0.026 | 0.046 |
| **Total liability** | 247,811 | 0.537 | 0.254 | 0.339 | 0.538 | 0.729 |
| **Short-term debt** | 230,038 | 0.039 | 0.075 | 0.000 | 0.010 | 0.042 |
| **Long-term debt** | 245,864 | 0.182 | 0.191 | 0.009 | 0.123 | 0.301 |
| **Debt ratio** | 194,395 | 0.255 | 0.312 | 0.020 | 0.113 | 0.376 |
| **Short-term debt volatility** | 247,057 | 0.038 | 0.059 | 0.010 | 0.024 | 0.048 |
| **Cost of debt** | 158,954 | 0.019 | 0.032 | 0.009 | 0.013 | 0.019 |
| **Dividend ratio** | 246,552 | 0.003 | 0.007 | 0.000 | 0.000 | 0.003 |
| **Cash holdings** | 247,833 | 0.177 | 0.213 | 0.029 | 0.090 | 0.243 |
| **Lagged Ln(assets)** | 248,046 | 6.569 | 2.358 | 4.891 | 6.710 | 8.211 |
| **Lagged BM** | 248,040 | 0.695 | 0.657 | 0.303 | 0.536 | 0.869 |
| **Lagged PPE** | 236,370 | 0.230 | 0.246 | 0.039 | 0.135 | 0.339 |
| **Lagged ROA** | 247,850 | -0.002 | 0.051 | -0.003 | 0.006 | 0.019 |
| **Lagged Investment** | 246,961 | 0.009 | 0.014 | 0.001 | 0.005 | 0.012 |

## Table II. Correlation Matrix

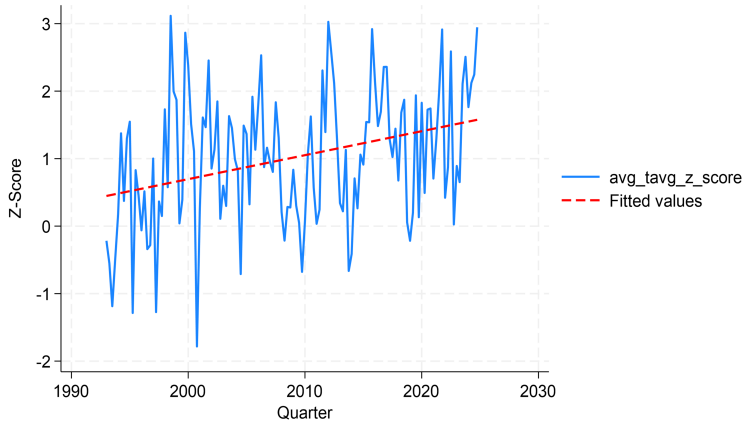
This table presents the correlation matrix between our final sample's variables, including both cash flow weather induced volatility measures and financial variables. The sample covers 248,049 observations for the period Q1 2002 to Q4 2023. Cash flow volatility is the standard deviation of cash flow over the past 36 quarters (a rolling window of 36 quarters). The debt ratio is the fraction of short-term debt over long-term debt. Short-term debt volatility is measured as the standard deviation of short-term debt over the past 36 quarters. For a detailed explanation of variables, see Table A.I in the Appendix.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **(1) Aggregate weather volatility** | 1 | | | | | | | | | | | | | | | | | |
| **(2) Local weather volatility** | 0.886 | 1 | | | | | | | | | | | | | | | | |
| **(3) National weather volatility** | 0.912 | 0.676 | 1 | | | | | | | | | | | | | | | |
| **(4) Q-ratio** | 0.28 | 0.244 | 0.264 | 1 | | | | | | | | | | | | | | |
| **(5) Cash flow volatility** | 0.874 | 0.784 | 0.781 | 0.298 | 1 | | | | | | | | | | | | | |
| **(6) Total liability** | −0.251 | −0.217 | −0.231 | −0.305 | −0.283 | 1 | | | | | | | | | | | | |
| **(7) Short-term debt** | 0.048 | 0.051 | 0.031 | −0.079 | 0.059 | 0.277 | 1 | | | | | | | | | | | |
| **(8) Long-term debt** | −0.19 | −0.164 | −0.17 | −0.071 | −0.222 | 0.462 | −0.002 | 1 | | | | | | | | | | |
| **(9) Debt ratio** | 0.193 | 0.174 | 0.166 | −0.01 | 0.22 | −0.099 | 0.564 | −0.541 | 1 | | | | | | | | | |
| **(10) Short-term debt volatility** | 0.157 | 0.146 | 0.136 | −0.003 | 0.181 | 0.077 | 0.381 | 0.042 | 0.237 | 1 | | | | | | | | |
| **(11) Cost of debt** | 0.151 | 0.123 | 0.132 | 0.017 | 0.168 | −0.101 | −0.037 | −0.156 | 0.171 | 0.052 | 1 | | | | | | | |
| **(12) Dividend ratio** | −0.08 | −0.078 | −0.064 | 0.173 | −0.09 | −0.056 | −0.044 | 0.09 | −0.088 | −0.055 | −0.074 | 1 | | | | | | |
| **(13) Cash holdings** | 0.37 | 0.337 | 0.335 | 0.406 | 0.415 | −0.411 | −0.145 | −0.314 | 0.123 | −0.038 | 0.07 | −0.053 | 1 | | | | | |
| **(14) Lagged Ln(assets)** | −0.455 | −0.406 | −0.405 | −0.197 | −0.516 | 0.445 | −0.021 | 0.332 | −0.305 | −0.128 | −0.187 | 0.129 | −0.374 | 1 | | | | |
| **(15) Lagged BM** | −0.076 | −0.061 | −0.074 | −0.448 | −0.075 | 0.035 | 0.101 | −0.052 | 0.104 | 0.07 | 0.027 | −0.163 | −0.168 | −0.065 | 1 | | | |
| **(16) Lagged PPE** | −0.125 | −0.12 | −0.106 | −0.049 | −0.143 | 0.015 | −0.008 | 0.345 | −0.227 | −0.035 | −0.051 | 0.068 | −0.296 | 0.103 | 0.023 | 1 | | |
| **(17) Lagged ROA** | −0.31 | −0.284 | −0.281 | −0.098 | −0.338 | 0.039 | −0.054 | 0.062 | −0.139 | −0.074 | −0.147 | 0.204 | −0.288 | 0.31 | −0.053 | 0.094 | 1 | |
| **(18) Lagged investment** | 0.006 | −0.004 | 0.009 | 0.084 | 0.005 | −0.066 | −0.058 | 0.104 | −0.135 | −0.035 | −0.019 | −0.002 | −0.112 | 0.01 | −0.111 | 0.598 | 0.092 | 1 |

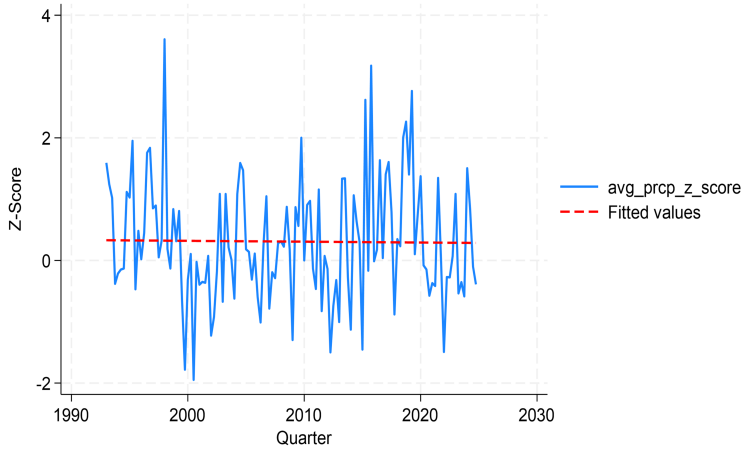
**Figure 1.** National Weather Changes and Trends

Plots (a) and (b) present the average national z-scores for temperature and precipitation in the U.S. from 1993 to 2024. The z-scores are computed using national monthly temperature and precipitation data from the National Oceanic and Atmospheric Administration (NOAA), aggregated to quarterly averages. For details on the z-score formulas and construction, see Section 3.2.1.

**(a)** Average National Temperature Z-score and Trend




**(b)** Average National Precipitation Z-score and Trend



## Table III. Uni-variate Regressions, WIV and Corporate Financing and cash Policies and Valuation

This table presents regression results for uni-variate regressions of financing policy, cash policy, and valuation variables on aggregate, local, and national weather induced volatility measures. All regressions have industry and year fixed effects. Standard errors are clustered in firm level. T-values are presented in parentheses below the coefficient estimates. *, **, *** indicate statistical significance at the p $<$ 0.10, 0.05, and 0.01, respectively. All tests are two-tailed.

**Panel A: Aggregate Weather Volatility (WIV)**

| | **Total liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** | **Div. ratio** | **Cash holdings** | **Q-ratio** |
|---|---|---|---|---|---|---|---|---|---|
| **Aggregate weather vol.** | -1.580*** | 0.365*** | -2.507*** | 5.403*** | 0.765*** | 0.353*** | -0.031*** | 3.757*** | 17.575*** |
| | (-9.051) | (6.291) | (-17.927) | (19.671) | (12.344) | (9.954) | (-5.881) | (19.872) | (11.303) |
| Observations | 245538 | 227940 | 243613 | 192714 | 244780 | 157530 | 244301 | 245559 | 245486 |
| Adj. $R^2$ | 0.3363 | 0.0538 | 0.2242 | 0.1133 | 0.0587 | 0.0515 | 0.1026 | 0.3495 | 0.2269 |

**Panel B: Local Weather Volatility (WIV)**

| | **Total liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** | **Div. ratio** | **Cash holdings** | **Q-ratio** |
|---|---|---|---|---|---|---|---|---|---|
| **Local weather vol.** | -1.648*** | 0.485*** | -2.754*** | 6.237*** | 0.916*** | 0.374*** | -0.040*** | 4.299*** | 18.234*** |
| | (-7.563) | (6.449) | (-15.744) | (18.163) | (11.142) | (8.459) | (-6.784) | (18.129) | (9.585) |
| Observations | 245538 | 227940 | 243613 | 192714 | 244780 | 157530 | 244301 | 245559 | 245486 |
| Adj. $R^2$ | 0.3343 | 0.0540 | 0.2171 | 0.1053 | 0.0550 | 0.0468 | 0.1026 | 0.3395 | 0.2194 |

**Panel C: National Weather Volatility (WIV)**

| | **Total liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** | **Div. ratio** | **Cash holdings** | **Q-ratio** |
|---|---|---|---|---|---|---|---|---|---|
| **National weather vol.** | -1.817*** | 0.308*** | -2.678*** | 5.539*** | 0.793*** | 0.365*** | -0.028*** | 4.004*** | 20.361*** |
| | (-9.151) | (4.940) | (-17.116) | (17.933) | (11.328) | (9.916) | (-4.421) | (18.896) | (11.246) |
| Observations | 245538 | 227940 | 243613 | 192714 | 244780 | 157530 | 244301 | 245559 | 245486 |
| Adj. $R^2$ | 0.3358 | 0.0520 | 0.2191 | 0.1035 | 0.0525 | 0.0477 | 0.1012 | 0.3400 | 0.2255 |

## Table IV. Aggregate Weather Induced Volatility Regressions, Financing Policy

This table shows the association between Aggregate Weather Risk and firms' financing policies. Aggregate Weather Vol is the aggregate weather induced volatility, which measures a firm's cash flow risk with respect to both local and national weather changes (see equation (12)). Detailed variable definitions are provided in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Total Liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** |
|---|---|---|---|---|---|---|
| **Aggregate Weather vol.** | 0.242 | 0.297*** | -0.447*** | 2.242*** | 0.563*** | 0.177*** |
| | (1.377) | (4.932) | (-3.825) | (8.948) | (9.239) | (5.066) |
| **Lagged log assets** | 0.034*** | 0 | 0.026*** | -0.037*** | -0.002*** | -0.001*** |
| | (28.029) | (0.08) | (27.187) | (-24.288) | (-5.089) | (-12.995) |
| **Lagged BM ratio** | -0.024*** | 0.009*** | -0.006** | 0.025*** | 0.006*** | 0 |
| | (-8.256) | (8.072) | (-2.472) | (6.641) | (5.977) | (0.909) |
| **Lagged ROA** | -0.663*** | -0.092*** | -0.297*** | -0.141*** | -0.028** | -0.065*** |
| | (-20.229) | (-9.287) | (-14.214) | (-3.222) | (-2.052) | (-8.326) |
| **Lagged PPE** | 0.123*** | 0.011** | 0.218*** | -0.185*** | -0.003 | -0.004*** |
| | (7.76) | (2.168) | (15.36) | (-11.409) | (-0.628) | (-3.795) |
| **Lagged investment** | -0.605*** | -0.213*** | -0.626*** | -0.291** | -0.028 | -0.046*** |
| | (-4.578) | (-5.567) | (-5.246) | (-1.994) | (-0.92) | (-3.857) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 232,784 | 222,043 | 230,879 | 187,336 | 232,514 | 152,751 |
| **Adj. $R^2$** | 0.4142 | 0.0578 | 0.2953 | 0.1854 | 0.0631 | 0.0713 |

## Table V. Local Weather Induced Volatility Regressions, Financing Policy

This table shows the association between Local Weather Risk and firms' financing policies. Local Weather Vol is the local (county of HQ) cash flow weather induced volatility, (see equation (12)). Detailed variable definitions are provided in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Total Liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** |
|---|---|---|---|---|---|---|
| **Local Weather vol.** | 0.490** | 0.381*** | -0.312** | 2.406*** | 0.638*** | 0.162*** |
| | (2.223) | (5.007) | (-2.167) | (7.942) | (8.361) | (3.779) |
| **Lagged log assets** | 0.034*** | 0 | 0.026*** | -0.038*** | -0.002*** | -0.002*** |
| | (28.591) | (-0.086) | (28.035) | (-25.412) | (-6.065) | (-14.256) |
| **Lagged BM ratio** | -0.024*** | 0.009*** | -0.006** | 0.024*** | 0.006*** | 0 |
| | (-8.253) | (7.987) | (-2.330) | (6.348) | (5.691) | (0.616) |
| **Lagged ROA** | -0.660*** | -0.093*** | -0.288*** | -0.164*** | -0.034** | -0.068*** |
| | (-20.204) | (-9.485) | (-13.827) | (-3.747) | (-2.467) | (-8.485) |
| **Lagged PPE** | 0.124*** | 0.010** | 0.220*** | -0.192*** | -0.004 | -0.005*** |
| | (7.846) | (2.098) | (15.548) | (-11.817) | (-0.939) | (-4.356) |
| **Lagged investment** | -0.608*** | -0.210*** | -0.640*** | -0.250* | -0.019 | -0.042*** |
| | (-4.606) | (-5.488) | (-5.358) | (-1.717) | (-0.630) | (-3.536) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 232,784 | 222,043 | 230,879 | 187,336 | 232,514 | 152,751 |
| **Adj. $R^2$** | 0.4144 | 0.0578 | 0.2948 | 0.1838 | 0.0609 | 0.0699 |

## Table VI. National Weather Induced Volatility Regressions, Financing Policy

This table shows the association between National Weather Risk and firms' financing policies. National Weather Vol is the national (county of HQ) cash flow weather induced volatility, (see equation (12)). Detailed variable definitions are provided in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Total Liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** |
|---|---|---|---|---|---|---|
| **National Weather vol.** | 0.039 | 0.221*** | -0.530*** | 2.145*** | 0.554*** | 0.164*** |
| | (0.208) | (3.555) | (-4.260) | (7.648) | (8.260) | (4.798) |
| **Lagged log assets** | 0.034*** | 0 | 0.026*** | -0.039*** | -0.002*** | -0.002*** |
| | (28.162) | (-0.495) | (27.740) | (-25.429) | (-6.169) | (-14.771) |
| **Lagged BM ratio** | -0.024*** | 0.009*** | -0.006** | 0.025*** | 0.006*** | 0 |
| | (-8.358) | (7.963) | (-2.470) | (6.525) | (5.842) | (0.817) |
| **Lagged ROA** | -0.672*** | -0.097*** | -0.295*** | -0.164*** | -0.034** | -0.067*** |
| | (-20.534) | (-9.884) | (-14.182) | (-3.764) | (-2.499) | (-8.427) |
| **Lagged PPE** | 0.121*** | 0.009* | 0.218*** | -0.192*** | -0.005 | -0.005*** |
| | (7.622) | (1.844) | (15.452) | (-11.820) | (-1.004) | (-4.183) |
| **Lagged investment** | -0.593*** | -0.206*** | -0.627*** | -0.264* | -0.022 | -0.044*** |
| | (-4.489) | (-5.395) | (-5.257) | (-1.808) | (-0.704) | (-3.685) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 232,784 | 222,043 | 230,879 | 187,336 | 232,514 | 152,751 |
| **Adj. $R^2$** | 0.4141 | 0.0566 | 0.2953 | 0.1837 | 0.0599 | 0.0702 |

## Table VII. Weather Induced Volatility Regressions, Cash and Dividend Policies

This table shows the association between Aggregate, Local, and National Weather Induced volatility measures (WIV) and firm's dividend and cash policies. Detailed variable definitions are available in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Dividend ratio** | **Cash holdings** | **Dividend ratio** | **Cash holdings** | **Dividend ratio** | **Cash holdings** |
|---|---|---|---|---|---|---|
| **Aggregate Weather vol.** | 0 | 1.808*** | | | | |
| | (-0.081) | (10.306) | | | | |
| **Local Weather vol.** | | | -0.005 | 2.016*** | | |
| | | | (-0.860) | (9.631) | | |
| **National Weather vol.** | | | | | 0.003 | 1.802*** |
| | | | | | (0.594) | (9.726) |
| **Lagged log assets** | 0*** | -0.009*** | 0*** | -0.010*** | 0*** | -0.010*** |
| | (3.941) | (-7.676) | (3.851) | (-8.660) | (4.126) | (-8.744) |
| **Lagged BM ratio** | -0.002*** | -0.042*** | -0.002*** | -0.043*** | -0.002*** | -0.042*** |
| | (-19.683) | (-19.051) | (-19.655) | (-19.345) | (-19.696) | (-19.135) |
| **Lagged ROA** | 0.020*** | -0.377*** | 0.020*** | -0.395*** | 0.020*** | -0.395*** |
| | (13.906) | (-11.037) | (13.938) | (-11.401) | (13.946) | (-11.543) |
| **Lagged PPE** | 0.002*** | -0.203*** | 0.002*** | -0.208*** | 0.002*** | -0.209*** |
| | (3.520) | (-18.764) | (3.456) | (-19.406) | (3.604) | (-19.490) |
| **Lagged investment** | -0.027*** | 0.040 | -0.027*** | 0.070 | -0.027*** | 0.061 |
| | (-6.877) | (0.522) | (-6.825) | (0.903) | (-6.923) | (0.793) |
| **Lagged leverage** | -0.003*** | -0.242*** | -0.003*** | -0.242*** | -0.003*** | -0.240*** |
| | (-10.167) | (-28.591) | (-10.162) | (-28.614) | (-10.185) | (-28.309) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 232,065 | 232,809 | 232,065 | 232,809 | 232,065 | 232,809 |
| **Adj. $R^2$** | 0.138 | 0.4642 | 0.138 | 0.4623 | 0.138 | 0.4619 |

## Table VIII. Weather Induced Volatility Regressions, Valuation Q-ratio

This table shows the association between Aggregate, Local, and National Weather Induced volatility and firm's valuation, Q-ratio. Detailed variable definitions are available in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Q_ratio** | **Q_ratio** | **Q_ratio** |
|---|---|---|---|
| **Aggregate Weather vol.** | 13.906*** | | |
| | (9.741) | | |
| **Local Weather vol.** | | 13.695*** | |
| | | (8.159) | |
| **National Weather vol.** | | | 15.453*** |
| | | | (9.481) |
| **Lagged log assets** | -0.023*** | -0.032*** | -0.029*** |
| | (-2.903) | (-4.095) | (-3.638) |
| **Lagged BM ratio** | -0.876*** | -0.883*** | -0.877*** |
| | (-34.338) | (-34.324) | (-34.361) |
| **Lagged ROA** | 0.085 | -0.098 | -0.001 |
| | (0.207) | (-0.237) | (-0.003) |
| **Lagged PPE** | -0.228*** | -0.279*** | -0.259*** |
| | (-2.855) | (-3.499) | (-3.248) |
| **Lagged investment** | 6.995*** | 7.287*** | 7.088*** |
| | (9.079) | (9.436) | (9.156) |
| **Lagged leverage** | -0.942*** | -0.940*** | -0.930*** |
| | (-14.609) | (-14.548) | (-14.452) |
| **Industry FE** | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm |
| **Observations** | 232,724 | 232,724 | 232,724 |
| **Adj. $R^2$** | 0.3674 | 0.3632 | 0.3663 |

# 9. Appendix

## Table A.I. Variable Definition

| Variable | Definition |
|---|---|
| **Size** | Calculated as the natural logarithm of quarterly market capitalization, which is calculated as closing price at the end of a quarter (PRCCQ) multiplied by the number of shares outstanding at the end of a quarter (CSHOQ) obtained from Compustat. |
| **Cash Flow** | Calculated as Quarterly Operating Activity - Net Cash Flow (OANCFY) divided by total assets of the quarter (ATQ) obtained from Compustat. ONACFY is reported as year-to-date value in Compustat. We adjust it to quarterly value before scaling by ATQ. |
| **Q-ratio** | Calculated as Market Capitalization(PRCCQ*CSHOQ) plus Quarterly Debt in Current Liabilities (DLCQ) plus Quarterly Total Long-term Debt (DLTTQ) divided by quarterly total assets (ATQ) obtained from Compustat. |
| **Cash holdings** | Calculated as the Cash and Short-term Investments (CHEQ) divided by total assets of last four quarter (ATQ) obtained from Compustat. |
| **Total liability** | Calculated as the Quarterly Total Liabilities (LTQ) devided by total assets of last quarter (ATQ) obtained from Compustat. |
| **Short-term debt** | Short-term debt. Calculated as the Quarterly Debt in Current Liabilities (DLCQ) divided by total assets of last quarter (ATQ) obtained from Compustat. |
| **Long-term debt** | Long_term debt. Calculated as the Quarterly Total Long-tem Debt (DLTTQ) divided by total assets of last quarter (ATQ) obtained from Compustat. |
| **Debt ratio** | Calculated as the fraction of short-term debt over long-term debt. |
| **Investment** | Calculated as the Quarterly Capital Expenditures (CAPXY) divided by total assets of last quarter (ATQ) obtained from Compustat. CAPXY is reported as year-to-date value in Compustat. We adjust it to quarterly value before scaling by ATQ. |
| **Dividend** | Calculated as the Quarterly Cash Dividend (DVY) divided by total assets of last quarter (ATQ) obtained from Compustat. DVY is reported as year-to-date value in Compustat. We adjust it to quarterly value before scaling by ATQ. |
| **Cost of debt** | Cost of debt. Calculated as the Quarterly Interest and Related Expense (XINTQ) divided by sum of (DLCQ) and (DLTTQ) obtained from Compustat. |
| **BM** | Book to Market Ratio. Calculated as the Quarterly Common/Ordinary Equity (CEQQ) divided by Market value of equity (PRCCQ) multiplied by (CSHOQ) obtained from Compustat. |
| **ROA** | Calculated as the Quarterly Income Before Extraordinary Items (IBQ) divided by total assets of last quarter (ATQ) obtained from Compustat. |
| **PPE** | Calculated as the Quarterly Property Plant and Equipment (PPENTQ) divided by total assets of last quarter (ATQ) obtained from Compustat. |
| **Cash flow volatility** | Calculated as the standard deviation of cash flow during the previous 36 quarters. |
| **Short-term debt volatility** | Calculated as the standard deviation of short-term debt during the previous 36 quarters. |

## Table A.II. Robustness, Uni-variate Aggregate Weather Exposure Regressions with WIV Dummy

This table presents the uni-variate association between aggregate weather induced volatility and firms' corporate policies, while including a dummy variable for the aggregate WIV values. The dummy variable equals 1 for firms with above median aggregate WIV and 0 for firms with below-median aggregate WIV. By including this dummy variable, we examine the association for highly risk versus low risk firms. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Total Liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** | **Dividend ratio** | **Cash holdings** | **Q-ratio** |
|---|---|---|---|---|---|---|---|---|---|
| **Aggregate Weather vol.** | 0.045 | -0.142 | 0.690 | -0.959 | 0.503*** | 0.245** | 0.002 | 1.829*** | 22.033*** |
| | (0.073) | (-0.721) | (1.358) | (-1.098) | (2.837) | (2.519) | (0.120) | (3.146) | (4.903) |
| **Dummy×Aggregate weather vol.** | -1.488*** | 0.464*** | -2.927*** | 5.766*** | 0.240* | 0.097 | -0.030** | 1.764*** | -4.080 |
| | (-2.702) | (2.660) | (-6.489) | (7.834) | (1.777) | (1.374) | (-2.058) | (3.687) | (-1.178) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 245538 | 227940 | 243613 | 192714 | 244780 | 157530 | 244301 | 245559 | 245486 |
| **Adj. $R^2$** | 0.3365 | 0.0541 | 0.2258 | 0.1155 | 0.0588 | 0.0516 | 0.1027 | 0.3500 | 0.2270 |

## Table A.III. Robustness, Multi-variate Aggregate Weather Exposure Regressions with WIV Dummy

This table presents the multi-variate association between aggregate weather induced volatility and firms' corporate policies, while including a dummy variable for the aggregate WIV values. The dummy variable equals 1 for firms with above median aggregate WIV and 0 for firms with below-median aggregate WIV. By including this dummy variable, we examine the association for highly risk versus low risk firms. Detailed variable definitions are available in Appendix A.I. Industry fixed effects are based on the Fama–French 48 industry classification. The sample period is from Q1 2002 to Q4 2023, and the data are at quarterly frequency. All variables are winsorized at the 1% and 99% levels. Standard errors are clustered at the firm level. t-values are shown in parentheses below the coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All tests are two-tailed.

| | **Total Liability** | **ST debt** | **LT debt** | **ST to LT debt** | **ST debt sd.** | **Cost of debt** | **Dividend ratio** | **Cash holdings** | **Q-ratio** |
|---|---|---|---|---|---|---|---|---|---|
| **Aggregate Weather vol.** | -1.710*** | -0.278 | 0.208 | -0.580 | 0.328** | 0.174* | 0.028* | 1.197** | 20.738*** |
| | (-2.995) | (-1.512) | (0.478) | (-0.746) | (1.993) | (1.866) | (1.920) | (2.410) | (5.248) |
| **Dummy×Aggregate weather vol.** | 1.802*** | 0.531*** | -0.605 | 2.581*** | 0.217* | 0.002 | -0.026** | 0.564 | -6.306** |
| | (3.634) | (3.272) | (-1.509) | (3.872) | (1.720) | (0.036) | (-2.036) | (1.370) | (-2.150) |
| **Lagged BM ratio** | -0.024*** | 0.009*** | -0.006** | 0.025*** | 0.006*** | 0.000 | -0.002*** | -0.042*** | -0.876*** |
| | (-8.233) | (8.093) | (-2.482) | (6.676) | (5.982) | (0.909) | (-19.695) | (-19.044) | (-34.350) |
| **Lagged PPE** | 0.125*** | 0.011** | 0.217*** | -0.183*** | -0.003 | -0.004*** | 0.002*** | -0.203*** | -0.234*** |
| | (7.855) | (2.255) | (15.327) | (-11.335) | (-0.592) | (-3.799) | (3.473) | (-18.662) | (-2.931) |
| **Lagged investment** | -0.608*** | -0.214*** | -0.624*** | -0.295** | -0.029 | -0.046*** | -0.027*** | 0.039 | 7.010*** |
| | (-4.612) | (-5.597) | (-5.233) | (-2.016) | (-0.935) | (-3.858) | (-6.865) | (0.507) | (9.105) |
| **Lagged ROA** | -0.666*** | -0.093*** | -0.296*** | -0.145*** | -0.029** | -0.065*** | 0.020*** | -0.378*** | 0.097 |
| | (-20.309) | (-9.403) | (-14.146) | (-3.329) | (-2.079) | (-8.343) | (13.924) | (-11.051) | (0.235) |
| **Lagged Leverage** | | | | | | | -0.003*** | -0.242*** | -0.939*** |
| | | | | | | | (-10.134) | (-28.613) | (-14.572) |
| **Industry FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Year FE** | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| **Cluster level** | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm | Firm |
| **Observations** | 232784 | 222043 | 230879 | 187336 | 232514 | 152751 | 232065 | 232809 | 232724 |
| **Adj. $R^2$** | 0.4146 | 0.0581 | 0.2954 | 0.1858 | 0.0632 | 0.0713 | 0.1381 | 0.4643 | 0.3675 |