Blame it on the weather: Market implied weather volatility and firm performance

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Abstract

We introduce a novel measure of weather risk implied from weather options' contracts. WIVOL captures risks of future temperature oscillations, increasing with climate uncertainty about physical events and regulatory policies. We find that shocks to weather volatility increase the likelihood of unexpected costs: a one-standard deviation change in WIVOL increases quarterly operating costs by 2%, suggesting that firms, on average, do not fully hedge exposures to weather risks. We estimate returns' exposure to WIVOL innovations and show that more negatively exposed firms are valued at a discount, with investors demanding higher compensations to hold these stocks. Firms' exposure to local but not foreign WIVOL predicts returns, which confirms the geographic nature of weather risks shocks.

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1 Introduction

The link between financial markets and extreme events stemming from climate related risks has been at the forefront in the news and academic community. Whether these shocks arise from physical damages caused by hurricanes or regulatory policies to transition to a less polluting economy, climate change is increasingly associated to the performance of different asset classes.

If climate change presents a material risk for firms' cash-flows and stock prices, then studying their exposure to weather related shocks presents a major challenge not only for the firms themselves, but also for investors and policy makers. This task is far from trivial. Existing analyses rely on firms' disclosures concerning their corporate policies towards an environmentally friendlier economy. The caveat is that these disclosures are mostly voluntary and can be purposefully misleading, as the Securities and Exchange Commission (SEC) notes. According to the SEC, few companies discuss about climate change and its more than a decade old guideline is in the process of being updated. Moreover, Morningstar notes that most companies do not disclose emissions data.[1] An alternative approach focuses on physical risks, which are based on historical weather events that can be rare and seasonal. For example, extreme heat events that are most likely to occur, and matter, during the summer months. Meanwhile, the primary objective is for companies to assess and mitigate their exposure to climate risk throughout the entire year.

In this paper, we adopt a fresh approach to examine climate risk. Rather than focusing only on ex-post extreme weather events, we explore the relevance of ex-ante weather volatility risk for financial markets. Our primary interest is in understanding investors' expectations

[1] "SEC Opens Review of Corporate Climate Change Disclosures," Wall Street Journal, February 24, 2021; "SEC to Hunt for Climate-Friendly Marketing That Misleads Investors," Wall Street Journal, March 4, 2021; "Carbon Emissions Data for Investors: Closing the Reporting Gap and Future-Proofing Estimations," Morningstar Sustainalytics, February 8, 2023.

about future temperature fluctuations and the extent to which firms are exposed to this risk.

Weather volatility risk can significantly impact firms' operating performance. Unusual temperature patterns, such as warmer-than-normal summers or colder-than-normal winters, can result in unexpected operating costs due to heightened energy demand, disruptions in distribution channels, and decreased labor and capital productivity. Abnormal temperatures can influence local power plants, leading to service outages that add to the disruptions faced by these firms (Shive (2012)). Extreme temperatures affect firms' performance by negatively impacting employees' mental and physical health, consequently affecting creativity, productivity and decision making abilities (Addoum, Ng and Ortiz-Bobea (2023)). Even less extreme temperature fluctuations pose a non-trivial risk for companies. For example, Hewlett Packard Enterprise's CEO Antonio Neri highlighted that HPE "projected scenarios for non-extreme weather events, finding than even small temperature increases (below 2 degrees Celsius) are important and could cost $200 million to the company".[2] Buildings also play a major role in climate change, contributing to approximately one-third of global energy consumption and one-quarter of carbon dioxide (CO2) emissions. Heating Ventilation and Air Conditioning (HVAC) systems concentrate 38% of buildings' energy consumption, with nearly half of it attributed to non-residential buildings (Gonzalez-Torres, Perez-Lombard, Coronel, Maestre and Da (2022)).

We present a new approach to measure weather risk, which encompasses both extreme and non-extreme weather events. We use weather option prices to estimate the time series for the implied weather volatility, which we denote WIVOL. Option contracts provide unique insights into investors' ex-ante beliefs on weather risk. The weather implied volatility (WIVOL) is estimated using weather option contracts traded at the Chicago Mercantile

[2] "Companies' Climate Risks Are Often Unknown. Here's How One Opened Up," Wall Street Journal, March 14, 2021

Exchange Group Inc. (CME), whose payoffs depend on daily deviations (or degree-days) in temperature from 65 degrees Fahrenheit. The 65F benchmark is based on industry conventions for commercial buildings' management and considered the most comfortable for normal operations. To account for seasonal variations in temperature, the contracts are further classified into heating degree-days (HDD) and cooling degree-days (CDD) options. Intuitively, HDD measure the additional heating firms need to maintain normal operations in colder days during winter months and CDD measure the additional cooling firms need to maintain normal operations in warmer days during summer months. Unlike recent work by Shlenker and Taylor (2021) using weather futures prices to study trends related to global warming through CDD futures contracts, our research delves into the significance of weather risks. We estimate investors' expectations about future temperature volatility, implied by option prices, and test the exposure of firms to this forward-looking measure of weather risk. Since temperature is a geographic based measure, we focus our analysis for the city of New York, for which option contracts' temperatures are recorded at the weather station of the LaGuardia airport.

From January 2005 to July 2021, we estimate the weather option implied volatility (WIVOL) and uncover significant fluctuations over time. WIVOL exhibits varying patterns across different seasons and years, increasing at the onset of heightened uncertainty on physical and transition events. For example, WIVOL increases with the advent of Hurricane Sandy in 2012 but also during times of abnormally colder temperatures such as in early 2014 and 2021. WIVOL also changes with consistently higher than expected temperatures with no risk of physical damages, such as in late 2010. Notably, our findings indicate an upward shift in WIVOL around mid-2020, which coincides with increased concern from regulators about climate risks (see, for instance, Ramelli, Wagner, Zeckhauser and Ziegler (2021)). These findings suggest WIVOL seems to capture not only market expectations about physical risk events but also reflects the growing concerns about climate-related risks from federal agencies and policy makers.

We then utilize WIVOL to examine how firms are influenced by market expectations of weather risk. Specifically, we estimate the exposure (betas) of firms to innovations in WIVOL and analyze their predictive power for these firms' future performance. The underlying hypothesis is that firms with more negative exposure to WIVOL innovations are valued at a discount. The reasoning behind this is that if expectations of larger temperature fluctuations lead to a higher risk of unexpected costs for the company, then forward-looking investors might demand compensation for holding stocks with more negative WIVOL beta. Consequently, this gives rise to a negative relationship between a firm's beta and its future stock return. To assess the significance of weather volatility risk, we conduct our empirical analysis using the set of firms headquartered in the city of New York.

First, we investigate the impact of WIVOL shocks on firms' operating costs. Our analysis reveals significant results: a one-standard deviation increase in WIVOL corresponds to a 2% rise in the quarterly growth rate of operating costs. This finding suggests that, on average, firms do not fully hedge their exposures to temperature volatility. Furthermore, we document that this impact is almost twice as pronounced for firms with more negative exposure to WIVOL, which confirms our initial hypothesis. Additionally, our findings reveal a tendency among managers to shift investors' focus towards firms' vulnerability to climate change risks. This inclination becomes evident when WIVOL shocks lead to higher operating costs, as managers seem to *blame it on the weather* and attribute these challenges to weather-related events.

Second, we test the predictive power of WIVOL beta on stock returns. To this end, we form portfolios of stocks based on their previous month betas. Employing a long-short strategy that buys stocks with the most negative previous month WIVOL betas and sells those with the most positive, we achieve risk-adjusted annualized returns ranging from 4.3% to 5.4%. Additionally, we test the return effect of WIVOL beta at the individual firm level using Fama MacBeth regressions and find a significant negative relation between firms' betas and their future stock returns. In all, and since stock prices are determined by ex-ante discounted cash-flows, these results suggest that the option implied weather volatility (WIVOL) contains value-relevant information that is not captured by historical counterparts. By extracting expectations of future weather volatility, instead of relying on realized ex-post equivalent measures, investors more effectively estimate the degree of firms' exposure to weather risks.

It is worth noting that strategies hedging climate risk are largely based on signals derived from extreme weather events, which are more likely to be associated with the summer months (e.g., extreme heatwaves, hurricanes). In light of this, we investigate if the performance of the WIVOL beta strategy is actually, and only, a summer affair. One of the advantages of the WIVOL beta strategy is that it does not depend on the occurrence of extreme events that are likely seasonal and infrequent. For example, strategies based on extreme heat events that are likely to be of consideration during the summer can make the rebalancing of portfolios more challenging. Unlike such strategies, the WIVOL beta approach is available year-round, and allows for rebalancing every month of the year. After computing average returns for each month of the year using the beta long-short strategy, our analysis confirms that the performance of the WIVOL beta strategy is not limited to the summer months. Interestingly, we find that December yields the highest return, followed by the month of April. This observation suggests that the WIVOL beta strategy's effectiveness is not confined to a specific season and can be beneficial across various months of the year.

Finally, and given that WIVOL is a geographic based measure, we expect local firms to exhibit stronger exposure than non-local firms based in a different state. To explore the local aspect of WIVOL, we estimate the option implied volatility of weather for the Dallas-Fort-Worth metroplex, with temperatures recorded at the weather station in the Dallas Fort-Worth International airport. We find that, as in the case of New York, firms based in the Dallas Fort-Worth area are significantly exposed to innovations in the WIVOL of Dallas Forth-Worth. Greater negative exposure of firms to WIVOL predicts higher future returns, validating our initial hypothesis. Interestingly, our second set of results confirm the local nature of weather risks. When we estimate New York firms' betas with respect innovations in the WIVOL of Dallas Fort-Worth, the predictability of these betas is statistically insignificant. Likewise, estimating Dallas Fort-Worth based firms' exposure to innovations in the WIVOL of New York leads to no predictability of future returns. This outcome indicates that firms are indeed significantly exposed to uncertainty about weather volatility risks specific to the city in which they are based.

The structure of the papers is as follows. Section 2 discusses the literature related to the paper. Section 3 presents the main data sets used in the analysis. Section 4 presents the weather option implied volatility (WIVOL). Section 5 discusses the empirical results. Section 6 concludes.

2 Related Literature

While the topic on the interactions between climate events and financial markets is relatively new, there has been a great amount of interest and research in the field. Giglio, Kelly and Stroebel (2021) and Hong, Karolyi and Scheinkman (2020) provide an excellent review on this literature. We next describe the studies most related to our work and then discuss our contribution.

A growing literature investigates the exposure of different asset classes to climate risks. The asset classes include stocks, municipal and corporate bonds and real estate, while the climate risks considered are physical risks, transition risks or a combination of both. To determine the variable of interest governing these risks dynamics, the literature uses text-based techniques (e.g., financial statements, news articles, emissions disclosures) or historical extreme events (e.g., extreme heat, hurricanes, sea level rise).

Most studies find substantial effects of climate risk on investors' decisions and asset returns. Engle, Giglio, Kelly, Lee and Stroebel (2020) develop a text-based index using climate change news from the Wall Street Journal and find that ESG friendly stocks outperform with news coverage. Huynh and Xia (2021) find that this index predicts the cross-section of corporate bonds returns. Acharya, Johnson, Sundaresan and Tomunen (2022) find that several asset classes are exposed heat shocks. Goldsmith-Pinkham, Gustafson, Lewis and Schwert (2023) document the significant exposure of municipal bonds to sea level rise. Choi, Gao and Jiang (2020) use Google news search to find that, when temperature levels are abnormally high, investors pay more attention to global warming and stocks disclosing high levels of CO2 emissions underperform. Bolton and Kacperczyk (2021) use firms' voluntary disclosures of CO2 emissions and document that more polluting firms earn higher future returns, as they are more exposed to regulatory risks, and consistent with the findings of Hsu, Li and Tsou (2023). Alekseev, Giglio, Maingi, Selgrad and Stroebel (2022) combine extreme heat shocks with managers' SEC disclosures to determine the stocks to buy and sell. Sautner, van Lent, Vilkov and Zhang (2023) also develop a text-based approach to determine firms' exposure to climate change based on managers earnings calls disclosures. Firms' risk is also impacted by climate change. Ilhan, Sautner and Vilkov (2021) find that firms' risk increase with CO2 emissions, while Kruttli, Roth Tran and Watugala (2023) document that hurricanes also induce greater uncertainty on firms' returns.

Our study makes the following contributions to the literature on climate risk. First, instead of extreme weather risk, we study the impact of innovations to temperature volatility on firms. We find that an increase in the likelihood of observing temperatures colder than expected in the winter or warmer than expected in the summer leads to unexpected costs for the firm and it ultimately impacts its performance. Second, we introduce a novel measure of weather risk. We estimate the time series for the volatility of temperature implied by weather option prices, which we denote WIVOL. We find that firms with more negative exposure to WIVOL exhibit higher future returns. Third, we study, and confirm, the local nature of weather volatility. We find that firms are exposed to the volatility of weather in the area in which they are based only, a result that highlights the importance in distinguishing between global and local weather risk.

3 Data and Methodologies

We obtain data on weather derivatives from the Chicago Mercantile Exchange Group Incorporated (CME). CME weather derivatives are exchange-traded contracts whose payoff depends on the evolution of a weather-related variable for a specific geographic location and period of time. The contracts are in the form of futures and options on futures, while the weather variable is an index based on daily temperature.[3] We next define the variables used in the computation of the derivatives' payoff.

The daily temperature (in Fahrenheit degrees) is measured for a specific weather station and the weather index is in degree-days, which is the daily temperature deviation from 65 Fahrenheit degrees. We consider two degree-days cases. Heating degree-days (HDD) measures the deviation below 65 degrees, while cooling degree-days (CDD) measures the

[3] Alternative weather variables include rainfall, snowfall and frost.

deviation above 65 degrees. Intuitively, HDD measure the additional heating firms need to maintain normal operations during colder days (below 65F). CDD measure the additional cooling firms need to maintain normal operations during warmer days (over 65F).

Option contracts written on futures contracts are based on the degree-days index, and so is their strike price. The futures contracts are written on the cumulative degrees days over a specific period of time. HDD call and put options payoff with strike price K and with T days to maturity respectively take the form

$$\begin{aligned} C_T^{HDD} &= \max\left(\sum_{t=1}^{T} \max(65 - F_t, 0) - K, 0\right) \\ P_T^{HDD} &= \max\left(K - \sum_{t=1}^{T} \max(65 - F_t, 0), 0\right) \end{aligned}$$

Likewise, CDD call and put options payoff with strike price K and with T days to maturity respectively take the form

$$\begin{aligned} C_T^{CDD} &= \max\left(\sum_{t=1}^{T} \max(F_t - 65, 0) - K, 0\right) \\ P_T^{CDD} &= \max\left(K - \sum_{t=1}^{T} \max(F_t - 65, 0), 0\right) \end{aligned}$$

We focus on monthly HDD and CDD contracts, for which both futures and options on futures expire on the second business day after the futures contract month. The CME lists HDD contracts for the months of November, December, January, February and March plus the transition months of October and April. CDD contracts are listed for the months of May, June, July, August and September plus the transition months of October and April. For each trading day, we collect data on the contract expiration date, option price, futures price, strike price and option implied volatility. Using these inputs and U.S. Treasury bill rates, we confirm the contracts' option implied volatility following Black (1976) and discard observations violating the put-call parity and outside the 0-200 percent range (see, for example, Goyal and Saretto (2009) and Chabi-Yo, Doshi and Zurita (2023)).

To study market expectations of localized weather volatility, we focus our analysis on future weather oscillations for the city of New York given that it represents the most liquid contract (Schlenker and Taylor (2021)). Therefore, the degree-days are with respect to the Weather Bureau Army station located at the LaGuardia airport (WBAN 14732). In order to generate a time series for the monthly weather option implied volatility, we utilize option contracts that are at-the-money and with maturity closest to 30 days. In addition, we compute the average implied volatility between HDD and CDD contracts for the transition months of October and April. We follow this procedure for each day from January 2, 2005 to July 31, 2021, and then take the monthly average. The resulting variable is the one-month, at-the-money, weather option implied volatility (WIVOL) that we discuss in next Section.

Data with respect to firms' is obtained from CRSP and Compustat. We collect monthly observations on firms' stock price, market capitalization and corporate headquarter location (matching the firm's city, state and zip code) from CRSP. We collect quarterly accounting data from Compustat. For the period between January 2005 to July 2021, the sample contains 2,669 New York based firms, with an average (median) of 656 (651) firms per month. We discard stocks with a price per share less than $5 and firms with less than 24 monthly returns.

4 Weather Option Implied Volatility

Figure 1 plots the time series for WIVOL, the weather option implied volatility based on the temperature recorded at the LaGuardia airport in the city New York. The sample period is from January 2005 to July 2021. To construct the time series, we use closest to one month to maturity option contracts that are at-the-money. The time series reports the average monthly observation from daily traded contracts. The series exhibits an average of 26.1% (median of 23%) implied volatility of weather throughout the sample. When we contrast WIVOL with other risks measures, the findings suggests it is related to weather specific risks, which are location specific in nature. For example, we find that the correlation between WIVOL and aggregate stock market volatility index VIX is negative and equal to -4.5%. In addition, WIVOL correlation with the global warming news index of Engle, Giglio, Kelly, Lee and Stroebel (2020) is also negative and equal to -7.7%.

[Insert Figure 1 Here]

The time series exhibits substantial time variation. WIVOL, given its link to the second distributional moment of a random variable, captures expected future oscillations due to both large and small shocks. We observe major oscillations in times of uncertainty about hurricanes in the summer season and snowstorms in the winter season. In 2005, while New York was not directly impacted by major developments in the Atlantic ocean, including Hurricane Katrina, local weather developments impacted WIVOL. June of 2005 was designated the warmest June on record, with WIVOL reaching 58%. October 2005 was the wettest month on record, with almost double the amount of rain recorded in any October and causing local flooding. WIVOL climbed to 52.9%.

In 2010, WIVOL peaked to 80.4% for what would end up being New York's hottest summer on record. Interestingly, in this record-breaking season there was no cataclysm that defined the period but a consistently higher than expected temperature. A combination of record breaking heat combined with a strong backdoor cold front approaching the region from the northeast helped to provide a very unstable environment. Flooding disrupted New England, with stretches of Interstate 95, the main route linking Boston to New York, closed for days. Hurricane Earl generated most of the uncertainty in October 2010 but ultimately did not impact the area. However, the city Power Authority was criticized for excessive spending on emergency crews, which led increased power rates for New York buildings.

WIVOL reached its maximum value of 81.7% in September of 2012, preceding the arrival of hurricane Sandy in the following month. Large parts of the city and surrounding areas lost electricity for several days as a result of the storm, which killed 43 people in New York City. Rehse, Riordan, Rottke and Zietz (2019) document that increased uncertainty about material physical risks like the impact of Hurricane Sandy lowers market liquidity. The winter of 2014 also generated an increase in WIVOL, with utilities asking customers to cut power use in early January and natural gas prices soaring as a snowstorm brought freezing temperatures to the northeast of the country.

We continue to observe time variation throughout the sample, with an upward shift in mid-2020. The increase in WIVOL can be related to climate policies and regulations for the city, as the New York State Department of Financial Services urged New York-based insurance companies to better manage the risks they face from climate change.[4] Moreover, the agency states that it would start asking insurers in 2021 what steps they have taken as part of its examination process. This local policy event, combined with discussions at the federal level regarding a stronger stance from regulators towards climate change could have

[4] "New York Regulator Pushes Insurers on Climate Change," Wall Street Journal, September 22, 2020.

impacted WIVOL given the increased demand for hedging climate risks.[5] In 2021, WIVOL drastic increase in February of 2021 is consistent with local and national weather events during this month, the latter mostly driven by the Texas power crisis caused by the winter storm. New York experienced one of the snowiest Februaries on record, with the National Weather Service registering three significant weather events for New York. Winter weather emergency declaration restricted all non-emergency travel in early February as well as all flights cancellation in LaGuardia airport.

Overall, we observe that WIVOL seems to capture future temperature oscillations, with peaks before or at the onset of important physical weather risks. It also seems to be related to regulatory or transition risks, as the increased levels from the mid-2020 suggests.

5 Empirical Analysis

In this section, we first estimate firms' exposure to innovations in WIVOL. Second, we investigate on the impact WIVOL on firms' future operating performance. Third, we test firms' exposure to weather risks as a predictor of their future returns.

5.1 Firms Exposure to WIVOL

We estimate the exposure of firms to weather option implied volatility innovations (ΔWIVOL). Specifically, each month t and for each firm i, we estimate the $\beta^{\Delta WIVOL}$ of individual stocks using monthly rolling regressions of excess stock returns on ΔWIVOL

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{\Delta WIVOL} \Delta WIVOL_t + \beta_{i,t}^{X} X_t + \varepsilon_{i,t} \tag{5.1}$$

[5] A recent survey by Stroebel and Wurgler (2021) finds that investors identify regulatory risk as the most important climate risk to business in the short-term.

where $R_{i,t}$ is the excess return of firm i in month t, ΔWIVOL is the innovation in weather option implied volatility and X is a set of controls. The controls impose for the loading $\beta^{\Delta WIVOL}$ to be orthogonal to the stock market excess return and the historical temperature volatility.[6] We use a 36-month window in the estimation of $\beta^{\Delta WIVOL}$. The first set of betas are obtained using the sample from January 2005 to December 2007. We then use these monthly betas to predict stock returns in the following month (January 2008) and repeat this exercise until July 2021.

5.2 WIVOL and Operating Performance

Weather is considered a key driver for buildings' energy consumption since it affects energy demand for heating, ventilation, and air conditioning (HVAC). Furthermore, other weather dependent conditions, such as daylight and humidity have a great impact on the use of equipment and on the number of hours indoors (Gonzalez-Torres, Perez-Lombard, Coronel, Maestre and Da (2022)). In the U.S., large office buildings account for 65% of the total electricity use and 36% of total energy use, with heating and cooling building services generating 15% of worldwide greenhouse-gas emissions. Larger oscillations in temperature around normal levels can therefore have non-trivial effects on firms' cash-flows. And this also includes non-disaster events.

Given that WIVOL measures expectations of future temperature oscillations around normal levels, we next study the extent to which firms' costs are impacted by innovations to WIVOL. Our conjecture is that operating costs increase with positive innovations to WIVOL. Weather risk directly impacts firms, as temperatures outside the normal range increases op-

[6] We proxy for the historical volatility of temperature with the standard deviation of the year-over-year change in temperature in the last 36 months. Using alternative definitions for the computation of the historical volatility produces similar results. The historical volatility is based on NOAA daily temperatures for the LaGuardia airport.

erating costs due to higher demand for energy. But it also does it indirectly, impacting power plants in the area which during outages cannot supply services to these firms, creating further disruptions (Shive (2012)). Furthermore, we expect this result to be stronger among firms with more negative exposure to WIVOL. We obtain quarterly firms' operating costs (COGSQ) from Compustat and then compute the year-over-year growth in operating costs. Since the dependent variable is an accounting measure, we follow Petersen (2009) and test the impact of weather risk within a panel data framework. We implement quarterly panel predictive regressions where the dependent variable is the year-over-year growth in operating costs. The explanatory variable is lagged quarterly innovations in WIVOL, and we control for firms size (log of market capitalization). We compute t-statistics controlling for the firm-effect and clustering standard errors at the firm level to account for potential serial correlation in the residuals. Table 1 reports the results.

[Insert Table 1 Here]

In column 1, the coefficient for ΔWIVOL is positive and statistically significant, indicating that positive innovations to WIVOL lead to higher operating costs in the following quarter. The economic significance is very important: a one-standard deviation increase in ΔWIVOL results in a 2% increase in the quarterly growth rate in operating costs. This finding is consistent with Somanathan, Somanathan, Sudarshan and Tewari (2021), who show that temperatures outside expected intervals can generate unexpected costs. WIVOL measures precisely the risk of temperatures falling below 65 degrees Fahrenheit in the winter months or exceeding 65F degrees in the summer months, with the 65 figure based on industry conventions for normal building operations. Addoum, Ng and Ortiz-Bobea (2020) find that extreme weather events have insignificant effects on firms' establishment sales, suggesting that large corporations have the resources to withstand physical damages. In the case of firms' exposure to innovations in WIVOL, these shocks include also non-extreme events that can still impact firms due to unexpected operational costs. Our results on the relevance of weather shocks are consistent with Brown, Gustafson and Ivanov (2021), who document that severe winter weather has no impact on firms' sales but reduces firms' cash-flows by increasing operating costs.[7] Unlike severe winter weather shocks, WIVOL innovations encompass both extreme and non-extreme events and seem to be prevalent during all seasons.

Next, we investigate the effect on operating costs for a subset of firms. If WIVOL does impact future operating costs, we expect for the effect to be stronger in firms with more negative exposure to weather risks. Note that a firm with negative exposure indicates that as WIVOL increases its stock price decreases, and therefore its beta is negative. Therefore, we interact WIVOL with firms' beta to test this conjecture. To create the interaction, the betas are transformed to dummy variables. The dummy equals to 1 for firms with below median beta, and 0 otherwise. Note that in this exercise, the dummy equal to 1 is for below median and not above median betas. The interaction term is ΔWIVOL$\times\beta^{\Delta WIVOL} < Median$, and the expected interaction sign for the coefficient is positive. Column 2 of Table 1 reports the results for the interaction variable, with a positive and statistically significant coefficient.

Do managers blame firms' performance on the weather? The significant effect of weather volatility on firms' future costs suggests managers should consider this risk as non-trivial. To investigate this matter, we explore the relevance of WIVOL on managers' discussions concerning climate change during firms' upcoming earnings calls. We employ the company-level measure of exposure to climate change developed by Sautner, van Lent, Vilkov and Zhang (2023) as a proxy for the level of attention managers dedicate to climate change. We anticipate that positive shocks to WIVOL will lead to an increase in discussions about climate

[7] In Table A.1, we report that innovations to WIVOL have no significant effect on firms' sales but negatively impact their cash-flows.

change in the future, particularly within firms characterized by more negative exposure to WIVOL. This mirrors the case observed when considering operating costs.

Note that this analysis examines whether there is an increased focus from managers about firms' climate change exposure subsequent to positive shocks to the WIVOL metric, regardless of whether these managers implement policies to mitigate the said exposure. In Table 2, column 1 presents findings indicating that innovations to WIVOL lead to heightened discussions about climate change among managers on average for firms. Column 2 introduces an interaction between the change in WIVOL (ΔWIVOL) and the level of firms' exposure to this change, revealing that the influence of ΔWIVOL on managerial discussions is more pronounced among companies with more negative betas. These results imply that, following an episode of weather-related uncertainty shock, managers redirect the attention of investors toward their firms' susceptibility to risks arising from climate uncertainty. This is a means to explain the negative repercussions of these shocks on the companies' fundamentals in the future. This pattern also suggests that managers attribute potential underperformance of the firm to the impact of uncertainty stemming from weather shocks, thereby safeguarding their own professional standing.

[Insert Table 2 Here]

Taken together, the results in this section confirm our hypothesis that an increase in market expectations about future temperature volatility leads to an increase in firms' operating costs, with managers acknowledging the importance of weather risks, and with the overall impact particularly stronger for firms with more negative WIVOL exposure.

5.3 Firms Exposure and Expected Returns

Do firms' exposures (betas) to innovations in WIVOL help predict these firms' future returns? Intuitively, firms with more negative exposure to weather risks will perform poorly as WIVOL increases, and therefore investors demand a higher compensation to invest in these firms. Conversely, firms with more positive exposure provide a good hedge against weather risks, and therefore investors are willing to pay higher prices and accept lower future returns for them. If this reasoning manifests over time, then a strategy buying stocks with most negative exposure while selling stocks with most positive exposure will exhibit positive and statistically significant returns.

To construct the long-short strategy, we form quintile portfolios by sorting individual stocks based on their previous-month betas. The portfolio quintile 5 (high) contains stocks with the highest (most positive) $\beta^{\Delta WIVOL}$ during the previous month, while the portfolio quintile 1 (low) contains stocks with the lowest (most negative) $\beta^{\Delta WIVOL}$ during the previous month. The difference portfolio (low minus high) results from holding a long position in the low $\beta^{\Delta WIVOL}$ portfolio and a short position in the high $\beta^{\Delta WIVOL}$ portfolio. We implement and rebalance the long-short strategy on a monthly basis and for the sample period from January 2008 to July 2021. Table 3 reports the results for value-weighted portfolios. Specifically, the Table reports the average betas as well as annual raw returns and abnormal returns for each quintile portfolio and long-short strategy. By construction, since the portfolios are formed by ranking stocks on previous month exposures, quintile betas monotonically decrease from 0.69 for portfolio 5 to -0.62 for portfolio 1. For the long-short strategy, the average return difference between quintile 1 (Low) and quintile 5 (High) is statistically significant and equal to 0.38% per month with a five-lags Newey and West (1987) corrected t-statistic of 2.6. This result indicates that stocks in the lowest beta quintile generate 4.56%

higher annual returns compared to stocks in the highest beta quintile.

[Insert Table 3 Here]

We investigate the possibility that return predictability generated by $\beta^{\Delta WIVOL}$ decreases once we incorporate well established risk factors. We therefore account for the excess market return, the three factors of Fama and French (1994), the Carhart (1997) momentum factor, the five factors of Fama and French (2015) and the four factors of Hou, Xue and Zhang (2014). In columns 3 to 7 of Table 3, each entry reports the intercept (alpha) from the regression of the portfolio returns on a constant and a risk factor model. In all cases, the long-short strategy yields economically and statistically significant returns, with alphas ranging from 4.32% to 5.40% annual, even after controlling for different risk factors.

These results suggest that sorting equity portfolios based on firms exposure to WIVOL innovations seems to provide significantly positive returns. In addition, the $\beta^{\Delta WIVOL}$ strategy provides diversification benefits, given the correlation between WIVOL and VIX and the global warming news index from Engle, Giglio, Kelly, Lee and Stroebel (2020), as we document in Section 4. Strategies that hedge climate risks based on extreme events can be challenging to rebalance frequently. This is the case since extreme events can be rare and also seasonal, such as the case of extreme hot temperatures or hurricanes, usually during the summer months. Firms, however, are exposed to uncertainty about temperature volatility year-round. The long-short $\beta^{\Delta WIVOL}$ strategy provides an alternative that can be implemented every month of the year. However, a valid concern is if the $\beta^{\Delta WIVOL}$ strategy is a summer affair. If its performance is mostly driven by extreme, seasonal events during the summer, we expect for its return to originate mostly in the summer months. To test this hypothesis, we compute the average return for each month of the year during our sample. Figure 2 confirms that the performance of the strategy is not a summer affair, with December (106 monthly basis points) representing the month with largest return, followed by the month of April (86 monthly basis points).

[Insert Figure 2 Here]

We further look into the return effect of $\beta^{\Delta WIVOL}$ at the individual instead of portfolio level. We examine the cross-sectional relation between expected returns and lagged betas at the stock level using Fama and MacBeth (1973) regressions. We compute the time-series averages of the slope coefficients from the regressions of one-month-ahead stock returns on the beta. The average slopes provide standard Fama-MacBeth tests for determining if the explanatory variable has, on average, nonzero premium. Table 4 reports the time-series averages of the slope coefficients and the Newey-West t-statistics in parentheses. The univariate regression results reported in column 1 indicate a negative and statistically significant relation between the beta and the cross-section of future stock returns. Column 2 controls for the firm's size (log of market capitalization) and also reports a significant loading with the expected sign. In line with results at the portfolio level, firms with lower $\beta^{\Delta WIVOL}$ exhibit higher future returns. Sautner, van Lent, Vilkov and Zhang (2023b) document that managers discussions on climate change do not seem to predict the realized future return of these firms. Their non-result could be an indication that, despite managers' discussing on climate change, they seem to *blame it on the weather* instead of implementing hedging policies. This is also consistent with the significant return effect of $\beta^{\Delta WIVOL}$, since its relevance suggests that managers do not fully hedge weather risk exposure.

[Insert Table 4 Here]

Overall, we find significant results for the return effect of $\beta^{\Delta WIVOL}$.[8] The negative link between firms' beta and their future returns at the portfolio and individual level is consistent

[8]Following Ang, Hodrick, Xing and Zhang (2006), we re-estimate betas only including the market return

with an investors' intertemporal hedging motive. On the one hand, stocks with negative betas correlate negatively with increases in expected weather volatility; hence, investors demand extra compensation in the form of higher expected return to hold these stocks. On the other hand, stocks with positive betas correlate positively with increases in expected weather volatility. Since stocks with positive beta would be viewed as relatively safer assets at times of increased volatility, investors are willing to pay higher prices and accept lower expected returns.

5.4 Firms Exposure to Foreign Weather Risk

Section 4 documents that WIVOL seems to change with local physical and regulatory weather risks, while Section 5.3 finds that local firms exhibit significant exposure to innovations in WIVOL. We therefore expect for local firms to exhibit stronger WIVOL exposure than non-local firms, which are based in a different geographic location.

We test this local exposure hypothesis next. We implement a similar exercise but this time use option prices based on the temperatures recorded in the metro area of Dallas Fort-Worth (DFW) in the state of Texas.[9] As in the case of WIVOL for the city of New York, we collect CME data on prices for options, futures, strikes, expiration dates and implied volatilities. To generate the time-series for the weather option implied volatility WIVOL, we use closest to one month maturity contracts that are at-the-money. We then compute the exposure of local firms to WIVOL DFW. We restrict the set to firms headquartered only in the cities of Dallas and Fort-Worth, based on a firm's city, state and zip code attributes.

in equation (5.1.), since including additional controls can add noise to the estimation. We then re-compute the portfolio strategy and the cross-sectional regressions, and find that the significance of the beta return effect remains strong. We report these results in Table A.2 and Table A.3 respectively.

[9] Specifically, the contract's payoff is with respect to the temperature (in degree-days) measured at the Dallas Fort-Worth International (DFW) airport station (WBAN 03927).

For the sample period of January 2005 to July 2021 this generates a total of 441 firms, with an average (median) of 101 (105) firms per month. We then estimate the exposure of DFW firms to WIVOL DFW and test its predictive power. Following the argument of Section 5.3, the long-short strategy entails buying stocks with most negative betas while simultaneously selling stocks with most positive betas. We find that the long-short strategy generates positive and statistically significant returns, even after controlling for well established risk factors. We also test the significance of the beta return effect at the individual firm level with Fama-MacBeth predictive regressions and find a negative and statistically significant coefficient, indicating that, on average, firms with lower exposure to WIVOL exhibit higher future returns. These results, reported in Table A.4 and Table A.5 respectively, support the hypothesis that the exposure of local firms to innovations in local weather risk is significant and helps predict firms' future performance.

Several studies find that measures that track global weather events have a significant impact on geographically dispersed entities (see, for instance, Engle, Giglio, Kelly, Lee and Stroebel (2020) and Huynh and Xia (2021)). The local nature of WIVOL (based on the temperature of a geography specific weather station) provides an interesting tool to test the extent to which firms based in one area are impacted by innovations in weather volatility of a different area. Therefore, we next test whether market expectations of weather volatility for New York (Dallas) contain significant information about the future performance of firms based in Dallas (New York). Specifically, we link WIVOL measured for the city of New York to firms based in the Dallas Forth-Worth area. This produces betas for DFW firms with respect to innovations in the weather volatility of New York, which we use to predict future stock returns of firms in DFW. Likewise, we estimate betas for New York based firms using innovations in the weather volatility of the Dallas Fort-Worth area. We use these betas to predict the future stock returns of firms based in New York. If we find significant exposure, then the local risk hypothesis does not hold, as both measures of risk become indistinguishable.

We test this argument by sorting quintile portfolios, buying stocks with most negative exposure (quintile 1) and selling stocks with most positive exposure (quintile 5). Interestingly, we find insignificant return predictability in both cases. Betas constructed using New York weather volatility do not predict the future return of firms based in the Dallas Fort-Worth metro area. Likewise, betas estimated using DFW weather volatility do not predict the future return of New York based firms. We report these results in Table 5. This finding supports the argument that, while firms can be subject to global climate risks, local firms are more exposed to local weather risk than non-local firms. Tuzel and Zhang (2017) find that firms location affect firms risk through local factor prices such as real estate and labor, while Kruttli, Roth Tran and Watugala (2023) find that firms located in hurricane prone area exhibit higher volatility of returns. Our findings are of first order, as local firms with more negative exposure to local weather risk exhibit higher future returns.

[Insert Table 5 Here]

6 Conclusion

We investigate on the relevance of weather volatility for firms' performance. To the best of our knowledge, this is the first study using investors' expectations about weather risks, which can only be extracted using weather option prices. We denote this new, forward-looking variable WIVOL, the weather option implied volatility. We find that WIVOL captures markets expectations about future shocks to weather risk, increasing with the likelihood of physical events such as hurricanes and with discussions about regulations to transition to an environmentally friendlier economy.

We estimate firms' exposure to WIVOL innovations and test its predictive power. First, we find that innovations to WIVOL increase operating costs of the average firm, and this effect almost doubles for firms with more negative exposure to WIVOL. We then relate firms WIVOL exposure to their future returns. We argue that firms with more negative exposure to WIVOL innovations are valued at a discount because expectations of larger oscillations in temperatures lead to a higher risk of unexpected costs for the company. Investors therefore demand a weather risk compensation to hold these stocks. We find that weather volatility risks are priced, a long-short strategy that buys stocks with more negative exposure and sells stocks with more positive exposure generates significant returns after controlling for different risk factors. Moreover, unlike strategies based on extreme events that are likely seasonal, the WIVOL strategy can be implemented year-round. We also confirm that firms are significantly exposed to the volatility of weather of the area in which they operate only, as innovations to weather volatility of a different area do not predict their future returns.

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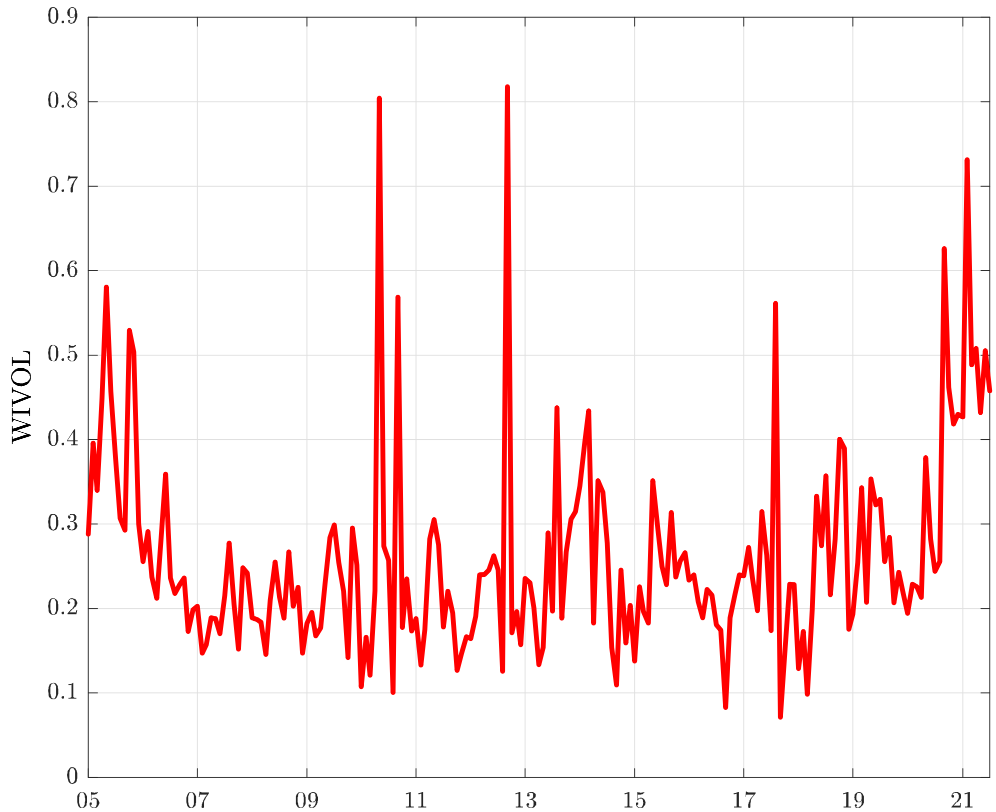
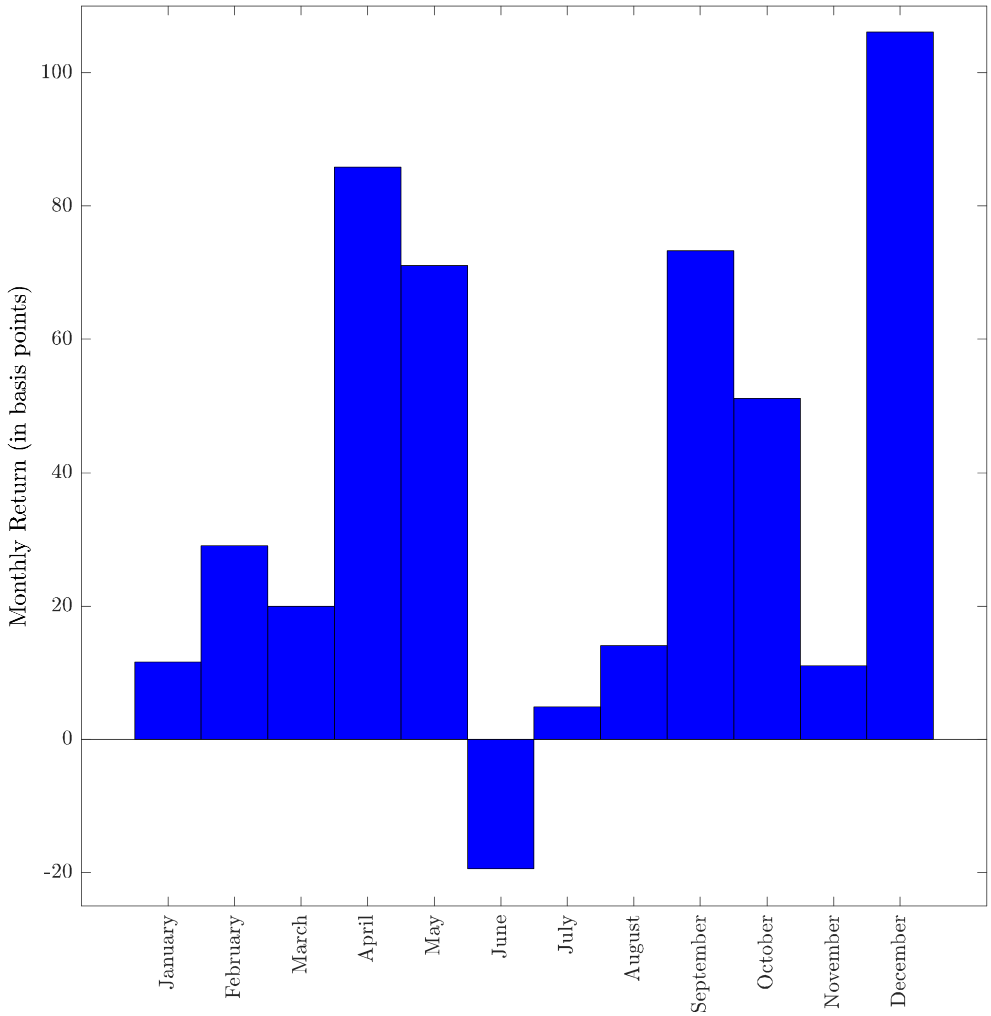
Figure 1: Weather Option Implied Volatility



We plot the time-series for WIVOL, the option implied volatility using weather options on futures contracts based on the temperature registered at the LaGuardia Airport in the city of New York. The time-series is constructed using one month to maturity contracts for at-the-money options. We report monthly average values. The sample period is from January 2005 to July 2021.

Figure 2: Average Return Strategy By Month



We plot average monthly returns for the long-short $\beta^{\Delta WIVOL}$ strategy. The strategy buys stocks with most negative $\beta^{\Delta WIVOL}$ and sells stocks with most positive $\beta^{\Delta WIVOL}$. The bar represents the average return (in basis points) in each month and for the sample period January 2008 to July 2021.

Table 1: WIVOL and Operating Costs

We report the quarterly panel regressions. The dependent variable is firms' year-over-year growth in quarterly operating costs (COGSQ). The sample is for firms based in the city of New York. The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. Column 1 reports the results for ΔWIVOL. Column 2 interacts ΔWIVOL with a dummy variable using firms' exposure to ΔWIVOL. The dummy variable equals to 1 for firms with below median $\beta^{\Delta WIVOL}$ and 0 otherwise. The regression also includes the dummy itself. The control variable is the firm's size defined as the log of the firm's market capitalization. We report in parentheses the t-statistics controlling for firm-fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged. The sample period is from January 2008 to July 2021.

Dependent Variable	Operating Costs Gr.	
	(1)	(2)
Intercept	-0.06	-1.28
	(-0.06)	(-1.34)
Size	0.15	0.34
	(0.99)	(2.27)
ΔWIVOL	6.65	2.10
	(4.57)	(1.03)
ΔWIVOL × $\beta^{\Delta WIVOL}$<Median		8.45
		(2.38)
R^2_{Adj}	0.31	0.35
N	30,208	26,785

Table 2: WIVOL and Climate Change Exposure

We report the quarterly panel regressions. The dependent variable is firms' quarterly Climate Change Exposure, as measured by managers' discussion on climate change during earnings calls and developed by Sautner, van Lent, Vilkov and Zhang (2023). The sample is for firms based in the city of New York. The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. Column 1 reports the results for ΔWIVOL. Column 2 interacts ΔWIVOL with a dummy variable using firms' exposure to ΔWIVOL. The dummy variable equals to 1 for firms with below median $\beta^{\Delta WIVOL}$ and 0 otherwise. The regression also includes the dummy itself. The control variable is the firm's size defined as the log of the firm's market capitalization. We report in parentheses the t-statistics controlling for firm-fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged. The sample period is from January 2008 to December 2020.

Dependent Variable	Climate Change Exposure	
	(1)	(2)
Intercept	-0.01	-0.04
	(-0.34)	(-1.70)
Size	0.01	0.02
	(4.82)	(6.05)
ΔWIVOL	0.19	0.01
	(2.12)	(0.09)
ΔWIVOL × $\beta^{\Delta WIVOL}$<Median		0.14
		(2.10)
R^2_{Adj}	0.72	0.73
N	17,632	17,168

Table 3: Portfolio Returns

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.68	2.76	2.52	2.04	2.04	1.92	2.28
		(1.63)	(1.48)	(1.08)	(1.09)	(1.04)	(1.31)
Q4	0.12	6.12	5.76	5.40	5.28	6.00	5.40
		(3.16)	(3.12)	(2.90)	(2.71)	(3.13)	(2.62)
Q3	0.02	6.36	5.88	6.36	6.36	6.24	6.00
		(3.52)	(3.98)	(4.30)	(4.42)	(4.32)	(4.15)
Q2	-0.07	6.24	6.00	5.76	5.64	6.00	5.64
		(3.37)	(3.54)	(3.26)	(3.10)	(3.29)	(2.93)
Low	-0.62	7.32	6.84	7.08	7.20	7.32	7.08
		(4.03)	(4.14)	(3.91)	(3.80)	(4.29)	(3.75)
Low-High		4.56	4.32	5.04	5.16	5.40	4.80
		(2.54)	(2.39)	(2.50)	(2.64)	(2.65)	(2.43)

Table 4: Firms Exposure and Return Predictability

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The dependent variable is the firm's monthly stock return. Column 1 reports the univariate regression using the benchmark explanatory variable, the firm's weather volatility exposure $\beta^{\Delta WIVOL}$. Column 2 controls for the firm's size defined as the log of the firm's market capitalization. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return	
	(1)	(2)
Intercept	0.36	0.12
	(2.80)	(0.98)
$\beta^{\Delta WIVOL}$	-0.07	-0.06
	(-2.28)	(-2.13)
Size		0.05
		(3.93)
R^2_{Adj}	0.01	0.02
N	114,872	114,872

Table 5: Firms exposure to foreign weather and return predictability

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges. Panel A estimates the exposure of firms based in the city of New York with respect to ΔWIVOL for the metro area of Dallas Fort-Worth. Panel B estimates the exposure of firms based in the metro area of Dallas Fort-Worth with respect to ΔWIVOL for the city of New York. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. New York firms exposure to Dallas Fort-Worth ΔWIVOL							
High	0.21	5.88	5.28	5.28	5.40	5.28	5.16
		(3.28)	(2.64)	(2.56)	(2.70)	(2.46)	(2.40)
Low	-0.18	5.04	4.68	4.44	4.32	4.56	4.20
		(2.98)	(3.21)	(2.69)	(2.52)	(2.72)	(2.43)
Low-High		-0.84	-0.72	-0.84	-1.08	-0.72	-0.96
		(-0.45)	(-0.35)	(-0.36)	(-0.51)	(-0.29)	(-0.41)
Panel B. Dallas Fort-Worth firms exposure to New York ΔWIVOL							
High	0.40	5.52	5.76	5.52	6.24	5.64	6.00
		(3.04)	(3.24)	(2.95)	(3.08)	(2.69)	(2.91)
Low	-0.38	5.28	5.16	5.16	5.04	4.92	4.56
		(2.95)	(2.80)	(2.72)	(2.72)	(2.69)	(2.38)
Low-High		-0.24	-0.48	-0.36	-1.20	-0.60	-1.44
		(-0.09)	(-0.24)	(-0.16)	(-0.53)	(-0.26)	(-0.59)

Table A.1: WIVOL and Operating Performance

We report the quarterly panel regressions. The dependent variable are firms' year-over-year growth in quarterly cash-flows (IBQ+DPQ) and sales (SALEQ). The sample is for firms based in the city of New York. The main explanatory variable is ΔWIVOL, the changes in the weather option implied volatility. Columns 1 and 2 report the results for cash-flows. Columns 3 and 4 report the results for sales. The control variable is the firm's size defined as the log of the firm's market capitalization. We report in parentheses the t-statistics controlling for firm-fixed effects and clustering standard errors at the firm level. All explanatory variables are one-quarter lagged. The sample period is from January 2008 to July 2021.

Dependent Variable	Cash-Flow Gr.		Sales Gr.	
	(1)	(2)	(3)	(4)
Intercept	-0.02	-0.02	0.01	-0.03
	(-1.42)	(-1.08)	(6.38)	(-1.48)
ΔWIVOL	-9.31	-8.62	-0.26	-0.10
	(-3.96)	(-4.23)	(-1.06)	(-0.81)
Size		0.00		0.01
		(0.53)		(2.07)
R^2_{Adj}	0.01	0.01	0.07	0.15
N	36,285	35,223	31,560	30,660

Table A.2: Estimation Robustness: Portfolio Returns

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Each firm's beta is estimated using the stock market return as control in the estimation of equation (5.1). Quintile 5 contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row reports the differences between portfolio 1 (Low) and portfolio 5 (High). The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.93	3.48	3.24	2.64	2.64	3.00	3.12
		(1.94)	(1.82)	(1.33)	(1.41)	(1.65)	(1.81)
Q4	0.11	6.72	6.24	6.00	5.88	6.36	5.76
		(3.45)	(3.56)	(3.40)	(3.17)	(3.24)	(2.89)
Q3	0.02	4.20	3.60	3.84	4.08	3.96	3.96
		(2.40)	(2.50)	(2.56)	(2.71)	(2.49)	(2.46)
Q2	-0.06	7.44	7.08	6.60	6.36	6.84	6.36
		(3.93)	(4.37)	(3.84)	(3.61)	(3.91)	(3.44)
Low	-0.95	7.56	7.08	7.44	7.68	7.56	7.56
		(4.26)	(4.44)	(4.26)	(4.23)	(4.36)	(4.23)
Low-High		4.20	3.84	4.80	4.92	4.56	4.44
		(2.30)	(2.03)	(2.22)	(2.35)	(2.10)	(2.09)

Table A.3: Estimation Robustness: Firms Exposure and Return Predictability

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the city of New York. The dependent variable is the firm's monthly stock return. The main explanatory is the firm's exposure to innovation in weather volatility risk $\beta^{\Delta WIVOL}$. Each firm's beta is estimated using the stock market return as control in the estimation of equation (5.1). Column 1 reports the univariate regression using the $\beta^{\Delta WIVOL}$. Column 2 controls for the firm's size defined as the log of the firm's market capitalization. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return	
	(1)	(2)
Intercept	0.36	0.12
	(2.79)	(0.97)
$\beta^{\Delta WIVOL}$	-0.09	-0.08
	(-2.12)	(-2.03)
Size		0.05
		(3.96)
R^2_{Adj}	0.00	0.02
N	114,872	114,872

Table A.4: Portfolio Returns (DFW)

We report the annualized returns for the value-weighted portfolios using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the metro area of Dallas Fort-Worth. Each month, quintile portfolios are formed by sorting individual stocks based on their previous month $\beta^{\Delta WIVOL}$. Quintile 5 (High) contains stocks with the highest $\beta^{\Delta WIVOL}$ during the previous month. Quintile 1 (Low) contains stocks with the lowest $\beta^{\Delta WIVOL}$ during the previous month. The bottom row (Low-High) reports the differences between portfolio 1 and portfolio 5. The columns report the betas, returns and abnormal returns (alphas). Column 1 reports the average $\beta^{\Delta WIVOL}$ per quintile. Column 2 reports the raw excess returns. Column 3 reports the abnormal returns α_{MKT} controlling for the market factor MKT. Column 4 reports the abnormal returns α_{FF3} controlling for the three factors in Fama and French (1993). Column 5 reports the abnormal returns α_{C4} controlling for the three factors in Fama and French (1993) and the Carhart (1997) factor. Column 6 reports abnormal returns α_{FF5} controlling for the five factors in Fama and French (2015). Column 7 reports abnormal returns α_{HXZ4} controlling for the four factors in Hou, Xue and Zhang (2014). We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

	$\beta^{\Delta WIVOL}$	Return	α_{MKT}	α_{FF3}	α_{C4}	α_{FF5}	α_{HXZ4}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High	0.40	-0.12	-0.12	-0.60	-0.72	-0.12	-0.84
		(-0.07)	(-0.08)	(-0.35)	(-0.40)	(-0.05)	(-0.46)
Q4	0.10	6.12	5.76	5.76	6.24	6.24	6.60
		(3.12)	(2.83)	(2.74)	(3.00)	(2.90)	(3.07)
Q3	0.01	6.96	6.96	6.84	6.84	6.36	6.36
		(2.94)	(3.06)	(2.98)	(2.97)	(2.64)	(2.67)
Q2	-0.07	2.64	2.16	3.24	3.00	3.24	2.64
		(1.10)	(0.92)	(1.42)	(1.35)	(1.43)	(1.15)
Low	-0.34	3.48	3.12	3.12	3.24	3.96	3.84
		(1.88)	(1.94)	(2.00)	(2.04)	(2.48)	(2.16)
Low-High		3.60	3.24	3.72	3.96	4.08	4.80
		(2.02)	(1.98)	(2.01)	(2.14)	(2.15)	(2.45)

Table A.5: Firms Exposure and Return Predictability (DFW)

We report the Fama-MacBeth cross-sectional regressions using common stocks in the NYSE, Amex, and Nasdaq exchanges for firms based in the in the metro area of Dallas Fort-Worth. The dependent variable is the firm's monthly stock return. Column 1 reports the univariate regression using the benchmark explanatory variable, the firm's weather volatility exposure $\beta^{\Delta WIVOL}$. Column 2 controls for the firm's size defined as the log of the firm's market capitalization. All explanatory variables are one-period lagged. We report in parentheses the Newey-West corrected t-statistics. The sample period is from January 2008 to July 2021.

Dependent Variable	Firm Return	
	(1)	(2)
Intercept	0.12	-0.28
	(1.35)	(-3.66)
β^{WIVOL}	-0.28	-0.29
	(-2.07)	(-2.04)
Size		0.07
		(3.88)
R^2_{Adj}	0.02	0.04
N	17,959	17,959