Weather Variance Risk Premia*

Joon Woo Bae† Kris Jacobs‡ Yoontae Jeon§

Stephen Szaura¶ Virgilio Zurita‖

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Abstract

We analyze the information content of a variance risk premia extracted from the CME's weather derivatives contracts written on the local temperature of U.S. cities. We refer to this metric as the Weather Variance Risk Premia (WVRP). By utilizing WVRP measures, we explore the impact of weather variance risk on bond credit spreads of local corporations and municipalities, as well as equity variance risk premium of local corporations. Our results highlight the informativeness of weather derivatives as an important factor in explaining the credit spreads of local corporations and municipalities. Our results are robust to controlling for state-level economic uncertainty measures.

JEL Classification: Q02, G13

Keywords: Weather Variance Risk Premia; Uncertainty; Municipal Bond; Corporate Bond; Stock Variance Risk Premia; Credit Spreads

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†Weatherhead School of Management, Case Western Reserve University, joon.bae@case.edu

‡Bauer College of Business, University of Houston, kjacobs@bauer.uh.edu

§DeGroote School of Business, McMaster University, yoontae.jeon@mcmaster.ca

¶BI Norwegian Business School, stephen.w.szaura@bi.no

‖College of Business and Analytics, Southern Illinois University, virgilio.zurita@siu.edu

1 Introduction

The recent surge in extreme weather events has significantly heightened public awareness of the real consequences of global warming. As a result, finance and economics literature is increasingly focusing on understanding the financial implications of risks associated with volatile weather outcomes. While evidence remains mixed on how and whether asset prices reflect weather risk, most studies concentrate on the *level* of temperature as a variable for quantifying such risk. However, it is the increased variance in temperature, such as extremely hot summers or abnormally cold winters, that has captured public attention. Therefore, contrary to existing studies, it seems logical to investigate how the time-varying variance of weather fluctuations affects asset prices, rather than focusing solely on the absolute temperature level. The primary challenge, then, is how to measure the time-varying weather variance risk, which is the main focus of our paper.

Over the last few decades, extensive research has demonstrated that the information embedded in options contracts provides a significantly deeper understanding of various financial markets. For example, the VIX index, constructed from S&P 500 index options, is now widely used by both academics and practitioners. Since the option prices are an outcome of risk-neutral pricing, these contracts help infer aggregate investors' risk preference. With the availability of empirical data of derivatives contracts, a substantial body of literature thus has emerged on risk preferences on higher moments of stock returns, such as variance risk premium. We build upon this established literature and use derivatives contracts written on the local weather conditions to extract investors' risk preference towards the weather variation.

While most of the focus has been on equity markets, we propose and construct weather variance measures from weather futures and options contracts traded on the Chicago Mercantile Exchange (CME). The underlying indices of these contracts are local temperature indices of various cities across the U.S.[1] Using a methodology similar to that employed in

[1]Recently, CME has also introduced weather derivatives in cities located at Europe and Asia.

equity options literature, we then compute the risk premium as the difference between the implied volatility of weather futures options and the volatility of weather futures. We term this measure the *Weather Variance Risk Premia* (WVRP), analogous to its definition in the equity options literature.

Our analysis is motivated by Carr and Wu (2009), who find that the cost of hedging stock return volatility risk inferred from equity options is higher than the estimated realized volatility (i.e., investors pay more to hedge stock return volatility risk than the risk they are exposed to), and Bollerslev, Tauchen, and Zhou (2009), who find that the market variance risk premia positively predict U.S. stock index returns. In a similar spirit, we interpret our WVRP measure as the cost of hedging local temperature fluctuations using weather derivative products and empirically analyze how it can help explain the local municipalities and firms' credit spreads, as well as local firms' equity variance risk premium.[2]

To empirically study this, we raise questions concerning the relationship between the weather variance risk premia and its impact on local firms and municipalities. A higher weather variance risk premia indicates investors' heightened risk aversion to local temperature fluctuations.[3] This suggests that investors fear the potential future impacts of natural disasters on the operations of firms and municipalities in the affected areas. We investigate this by examining three main measures: local municipal bond credit spreads, local corporate bond credit spreads, and the stock return variance risk premia of local corporations.

Building on the findings of Bollerslev, Tauchen, and Zhou (2009) and Chen, Doshi, and Seo (2023), who demonstrate that variance risk premia in stock and bond markets are positively related to expected returns, we hypothesize that weather variance risk premia will similarly influence local assets. Specifically, we expect weather variance risk premia to

[2] We define local municipalities and firms as those operate and headquartered in the cities where the underlying index of weather derivatives are measured at.

[3] The weather derivatives market has become increasingly important in hedging against temperature exposure and has seen a dramatic jump in the amount of trading in 2023 (Robertson (2023) and Potter (2024)). Additionally, the CME Group suite of weather derivatives has recently announced its expanded weather derivatives to newly the listed cities of Paris, Essen, Burbank, Houston, Philadelphia, and Boston (Balsamo and Krema (2023)). Also see Institute (2021).

have a positive contemporaneous impact on the credit spreads of municipalities and local firms and to positively predict the expected bond returns of these entities. To test these predictions, we conduct both contemporaneous and predictive regressions to assess whether weather derivatives risk premia have a positive contemporaneous impact on bond credit spreads and can predict positive expected returns.

Our principal findings reveal that our weather variance risk premia is positively contemporaneously priced in the local cross-section of stock return variance risk premia, as well as in corporate and municipal bond credit spreads. Our results indicate that a higher cost of hedging temperature volatility lead to a higher current cost of hedging equity volatility uncertainty and higher localized corporate and municipal credit spreads. These findings imply that a higher weather variance risk premia is associated with a greater cost of insuring against changes in the local firm's cash flow uncertainty induced by weather. Consequently, investors demand a lower price for corporate and municipal bonds since it becomes more costly to insure, resulting in increased current credit spreads. Additionally, we find that our weather variance risk premia is negatively priced in the expected future local cross-section of stock return variance risk premia, corporate, and municipal bond credit spreads. Our results suggest that a higher cost of hedging temperature volatility today leads to a lower expected future cost of hedging equity volatility uncertainty, as well as lower expected future localized corporate and municipal credit spreads.

A substantial body of literature has been developed and continues to evolve, focusing on how to measure economic uncertainty and its impact on the expected real and financial economy.[4] Recently Baker, Bloom, and Terry (2023) utilized various disaster measures to estimate the impact of uncertainty shocks on the macro economy. The impact of local uncertainty shocks has been shown to have a forward looking effect on local stock and corporate bond returns (see Bali, Brown, and Tang (2017) and Bali, Subrahmanyam, and Wen (2021)).

[4]Baker, Bloom, and Davis (2016) studies the impact of economic policy uncertainty across different nations whereas Baker et al. (2022) measure U.S. state level economic uncertainty.

Our paper contributes to three strands of literature: (1) climate and temperature uncertainty, (2) weather derivatives, and (3) variance risk premia. First, our paper contributes to the literature on climate and temperature uncertainty, as seen in works such as Weitzman (2009), Kruttli, Roth Tran, and Watugala (2023), Hain, Koebbel, and Leippold (2023), Barnett, Brock, and Hansen (2021), Bilal and Rossi-Hansberg (2023), Barnett (2023), and Barnett, Brock, and Hansen (2020) among many others. Several papers have documented the impact of temperature shocks on macroeconomic output and growth.[5] Acharya et al. (2022) study the premium in the cross-section of U.S. stocks and the spread component in corporate and municipal bonds for physical climate risk across all regions in the U.S., while Ginglinger and Moreau (2023) examine the impact of physical climate risk on firms' debt structure. Bansal, Kiku, and Ochoa (2021), Barnett (2023) and Donadelli et al. (2022) investigate the size of the premia required in the cross-section of U.S. stocks for temperature changes over recent decades.[6] Our findings suggest the benefits of hedging temperature volatility on the local financial economy. A seminal paper beginning the literature of the impact of local weather on asset prices is the impact of local Florida weather on orange juice futures (Roll (1984)).

Secondly, we contribute to the literature on weather derivatives, a class of securities whose payoff is contingent on the specific temperature at a particular city.[7] Several papers in this literature have examined the impact of the inception of an exchange to trade weather

[5]For the impact of temperature on economic growth see Bansal, Kiku, and Ochoa (2021), for the US Colacito, Hoffmann, and Pham (2019), as well as across different countries see Dell, Jones, and Olken (2012). For the impact of temperature volatility on growth see Donadelli et al. (2022) as well as Bortolan, Dey, and Taschini (2023) and the impact of heat waves on economic growth see Miller et al. (2021) as well as references therein. For impact on international trade see Jones and Olken (2010).

[6]This literature should not be confused with the impact of climate-related *ex-ante disasters* or the literature on flood risk for coastal municipalities. For the impact of climate related *ex-ante disasters* on municipal bond returns see Auh et al. (2023). For the impact of flood risk for coastal municipalities see Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Murfin and Spiegel (2020), Goldsmith-Pinkham et al. (2023), Giglio et al. (2023), and references therein.

[7]Additionally our work is tangently linked to the stream of literature on catastrophe bonds which are bonds whose payoffs are linked to the occurrence of pre-specified catastrophic events such as hurricanes or tornadoes, however, our weather derivatives are related to the payoff of specific temperatures at city airports. For the literature on catastrophe bonds see Froot (2001), Cummins, Lalonde, and Phillips (2004), Froot and O Connell (2008), Garmaise and Moskowitz (2009), and Tomunen (2023) amongst others.

derivatives on various aspects, including: (i) firm risk management practices in the utilities industry (see Perez-Gonzalez and Yun (2013)), (ii) the improvement of weather forecasting by government agencies (see Purnanandam and Weagley (2016)), and (iii) the impact of executive compensation for controllable weather risk (see Armstrong, Glaeser, and Huang (2022)). A seminal contribution to this literature is the work of Weagley (2019), who finds that limited financial intermediary risk-bearing capacity increases the prices of weather derivatives during times of market stress when intermediary capital is constrained. Another section of the weather derivatives literature has focused on pricing weather derivatives, beginning with (i) Cao and Wei (2004), Zhou, Li, and Pai (2019), and Hess (2024) who use stochastic models and general equilibrium approaches to price weather derivatives; (ii) Campbell and Diebold (2005), Dorfleitner and Wimmer (2010) Chincarini (2011), and Hardle, Lopez-Cabrera, and Teng (2016), who focus on pricing weather futures; (iii) Hardle and Lopez-Cabrera (2012) and Hardle, Lopez-Cabrera, and Teng (2015), who utilize weather options and futures for extracting the market-implied weather risk premia state price density; and (iv) Schlenker and Taylor (2021) who show that weather futures are priced consistently with market expectations about future weather conditions. Our contribution to this literature is to demonstrate the usefulness of weather derivatives in hedging a broad cross-section of local temperature variations, impacting the corresponding local underlying firm stocks, corporate bonds, and municipal bonds.[8]

The third literature our paper contributes to is the growing body of research on variance risk premia. Since the seminal findings of Carr and Wu (2009), which showed that the cost of hedging stock volatility risk inferred from equity options is higher than the estimated realized volatility (i.e., investors pay more to hedge stock volatility risk than the risk they are exposed to), and Bollerslev, Tauchen, and Zhou (2009), who demonstrated that variance risk premia positively predict U.S. stock index returns, a flurry of research has emerged to

[8] Our paper differs, but compliments, the findings from Bae et al. (2023) which find, using monthly weather futures options, their measure weather implied volatility increases firm quarterly operating costs by 2%.

study different forms of hedging and to understand variance risk across various asset classes.[9] Furthermore, Drechsler and Yaron (2011) and Drechsler (2013) have shown important connections between variance risk premia and understanding macroeconomic uncertainty and asset pricing puzzles. To this literature, our paper contributes a novel variance risk premia measure called Weather Variance Risk Premia (WVRP), derived from options on heating and cooling index seasonal strip weather futures.[10]

The rest of this paper is organized as follows: Section 2 outlines the data, Section 3 discusses stylized facts of weather options data, Section 4 presents the main findings, Section 5 provides several robustness checks, and Section 6 concludes.

2 Weather Futures and Options Data

We obtain main data from the Chicago Mercentile Exchange (CME). CME introduced standardized *monthly* weather futures and options contracts in 1999. The database provides end-of-day snapshot of volume, bid-ask price, open interest, and implied volatility, among many others. The monthly weather derivative contract's payoff is determined by the average daily temperature taken at the airport weather station at a specific city. Specifically, the payoff of the standard monthly temperature contracts are based on either a heating degree day (HDD) index or a cooling degree day (CDD) index for a specific city i during month t. The HDD contracts are listed and traded during the months of the traditional heating

[9]Different measures of variance risk premia have been developed for various asset classes as investors use derivatives on different underlying assets to hedge future asset risk. For example, variance risk premia is derived from U.S. Treasury interest rate futures (see Choi, Mueller, and Vedolin (2017)), corporate bond variance risk premia is developed using options on credit default swap indices (see Chen, Doshi, and Seo (2023)), and a similar term is developed in the commodity market (Heston and Todorov (2023)). See also, Bakshi and Kapadia (2003), Dew-Becker et al. (2017), Feunou, Jahan-Parvar, and Okou (2018), and Pyun (2019).

[10]The temperature and weather outcomes on firm financial performance have been documented in Addoum, Ng, and Ortiz-Bobea (2020), Addoum, Ng, and Ortiz-Bobea (2023), Brown, Gustafson, and Ivanov (2021), Griffin, Lont, and Lubberink (2023), Huynh and Xia (2021), Kirk, Stice, and Stice (2022), Pankratz and Schiller (2023), Pankratz, Bauer, and Derwall (2023), and Zhang (2023). For investors' perceived behaviour to weather events and climate change risk, see Busse et al. (2015), Dessaint and Matray (2017), Choi, Gao, and Jiang (2020), Engle et al. (2020), Goetzmann et al. (2020), Alekseev et al. (2022), Lontzek et al. (2023), Ilhan et al. (2023), Sautner et al. (2023), and Kruttli, Roth Tran, and Watugala (2023). Bergman, Iyer, and Thakor (2020) analyze the impact of local weather-driven cash flow shocks on the real and financial sectors.

season which runs from November through March. Correspondingly, the CDD contracts are listed and traded during the months of the traditional cooling season which runs from May through September. HDD and CDD index values for city i during month t are defined as

$$\text{HDD}_{i,t} = \sum_{d=1}^{D_t} \max[65 - T_{i,d}, 0] \qquad\qquad \text{CDD}_{i,t} = \sum_{d=1}^{D_t} \max[T_{i,d} - 65, 0], \tag{2.1}$$

where D_t is the number of days in month t and $T_{i,d}$ is the average temperature measured in degrees Fahrenheit of the minimum and maximum temperature for a specific city i on day d. The $\text{HDD}_{i,t}$ ($\text{CDD}_{i,t}$) are therefore the *monthly* HDD (CDD) indices for a specific city i during month t. The contract price quotes are in units of \$20, hence the payoffs of the HDD (CDD) indices are $20 \times \text{HDD}_{i,t}$ ($20 \times \text{CDD}_{i,t}$). Intuitively, HDD (CDD) index measures extra amount of heating (cooling) needed to keep the temperature above (below) 65 during the particular month. In other words, it conveniently tracks the amount of energy consumption needed to maintain the standard level of temperature instead of focusing on the average temperature over the month.

The CME also offers standardized *seasonal strip* HDD and CDD weather derivative contracts. A seasonal strip contract is based on the cumulative HDD or CDD values during a five-month period within the season. Seasonal strip contracts provide the same type of risk exposure as monthly HDD and CDD contracts, but offer the convenience of being traded as a bundled package of months during the heating or cooling season, hence provides a tool to hedge against entire season instead of rolling over the monthly contracts. In many cities, the traded volume of seasonal strips are order of magnitude larger than individual monthly derivative contracts for this reason.

All option contracts are written on weather futures (monthly and seasonal strip) prices, can only be exercised at contract maturity (i.e. European exercise style), and implied volatility (delta) of each contract price quote is computed using the Black (1976) model. As noted in Weagley (2019), the main purchasers of weather derivatives are energy and utility companies whereas the liquidity suppliers are financial institutions. Energy and utility companies take a short position in the temperature futures in order to hedge their risk exposure to changes in local temperature.

Our analysis in this paper will focus on two sets of weather derivatives. The first set will be the seasonal strip options and the second set will be their underlying seasonal strip HDD and CDD futures of the following cities: Atlanta/Georgia (ATL), Chicago/Illinois O'Hare (ORD), Cincinnati/Ohio (CVG), Dallas-Fort Worth/Texas (DFW), Las Vegas/Nevada (LAS), Minneapolis-Saint Paul/Minnesota (MSP), New York Laguardia/New York (LGA), and Sacremento/California (SAC). Table A.1 documents comprehensive information regarding the specific code used from the CME. The seasonal strip options and futures data set spans from January 2006 to December 2019.

We apply several standard filters to our seasonal strip futures and seasonal strip options data set before beginning our analysis. We remove option implied volatilities that are either (i) missing, (ii) equal to zero, or (iii) greater than 100%. Additionally, we remove futures and options quotes in which open interest is either zero or missing. Table 1 reports the sample statistics of the implied volatility, open interest, remaining days to maturity (d2mat), and remaining time to maturity (in years) for each of the CME Weather derivatives seasonal strip options used. Average seasonal strip option implied volatility ranges from 27% to 59% in the cross-section, and ranges from 10% (10^{th} percentile) to 91% (90^{th} percentile) in the distribution. The average days to maturity (d2mat) of the contracts is very similar across all contracts ranging from 92 to 112 days. The average open interest ranges from 706 to 1,153 units.

INSERT TABLE 1 HERE

The seasonal strip futures data set spans from January 2006 to December 2019. We compute average raw seasonal strip futures returns per city/state with the returns on the city/state being defined as the HDD futures returns during the November to April months and returns on CDD futures returns during the May to October months. Then, compute annualized seasonal strip return volatility from futures returns for each city/state as follows:

$$\text{WRVOL}_{c,t} = \begin{cases} \sqrt{\widehat{\mathbb{VAR}}\left(\frac{F_{HDD,c,d}-F_{HDD,c,d-1}}{F_{HDD,c,d-1}}\right)} & \text{if } t = \text{Nov.,...Apr.} \\ \sqrt{\widehat{\mathbb{VAR}}\left(\frac{F_{CDD,c,d}-F_{CDD,c,d-1}}{F_{CDD,c,d-1}}\right)} & \text{if } t = \text{May.,...Oct.} \end{cases}, \tag{2.2}$$

where $F_{HDD,c,d}$ ($F_{CDD,c,d}$) is the weather seasonal strip futures HDD (CDD) contract price on day d for city c which are only available during the months of Nov,...Apr (May,...Oct), respectively, and where $\sqrt{\widehat{\mathbb{VAR}}(\cdot)}$ is the sample volatility of the daily weather seasonal strip futures HDD (CDD) contract price $F_{HDD,c,d}$ ($F_{CDD,c,d}$) returns computed for each county c, across all days d of the calendar month t. The average annualized realized volatility of seasonal strip futures (WRVOL$_{c,t}$ for city/state c at time t) varies between 53% to 67% in the cross-section. It also shows significant variation across the time-series distribution that ranges from 13% (10^{th} percentile) to 193% (90^{th} percentile) that exhibits large positive skewness.

Next, we extract the weather seasonal strip options average option implied volatility (WIVOL$_{c,t}$) across all weather seasonal strip options for city c at time t for each month. Combining the two, We now can define our main measure of interest, the weather variance risk premia (WVRP$_{c,t}$), for each month t for each city c as the difference between the WIVOL$_{c,t}$ and WRVOL$_{c,t}$,

$$\text{WVRP}_{c,t} = \text{WIVOL}_{c,t} - \text{WRVOL}_{c,t}. \tag{2.3}$$

INSERT TABLE 2 HERE

Table 2 reports the weather seasonal strip variance risk premia, WVRP$_{c,t}$, as well as WIVOL$_{c,t}$ and WRVOL$_{c,t}$ for each city. Similar to the stock market, implied volatilities of weather derivatives are substantially greater than the realized volatilities for all cities in our sample, reflecting the positive price associated with the hedging against weather volatility risk. The resulting monthly weather variance risk premia is 0.29 on average with standard deviation of 0.22 and ranges from 0.04 (10^{th} percentile) to 0.61 (90^{th} percentile).

3 Characteristics of Weather Options

3.1 Stylized Facts

While there exists few papers who have used weather futures data, detailed discussion of weather options data were mostly absent in the prior literature. We therefore start by pointing out interesting observations from the weather options data. We first would like to emphasize that the futures and options data used in our paper are so called standardized *seasonal strip* HDD and CDD contracts offered by the CME. A seasonal strip contract is based on the cumulative HDD or CDD values during a five-month period within the corresponding season. Seasonal strip contracts provide the same type of risk exposure as monthly HDD and CDD contracts, but offer the convenience of being traded as a bundled package of months during the heating or cooling season, hence provides a tool to hedge against entire season instead of having have to roll over the monthly contracts. In many cities, the traded volume of seasonal strip contracts are order of magnitude larger than individual monthly derivative contracts for this reason.[11] For example, a separate HDD seasonal strip contract begins to cumulate in each of the months from November to March, and hence separate futures and options are available for each of the months. Analogously a separate CDD seasonal strip contract begins to cumulate in each of the months from May to September, and hence separate futures and options are available for each of the months. In many cities, the trading activity of the HDD (CDD) seasonal strips is largest in the November (May) seasonal strip contract instead of the other months coinciding with

[11] We would like to note that while the seasonal strip gives us richer cross-sectional observations due to this reason, monthly contracts are more popular than seasonal strips in some cities such as New York.

participants hedging at the beginning of the upcoming winter (summer) season month as oppose to the demand being closer to when the peaks of the cold (heat) can occur during the season.[12]

Table 1 provides summary statistics of the seasonal strip weather options contracts. First, the average open interest of weather futures contract, the underlying security, is significantly larger than the rest for Atlanta, followed by New York, then smaller magnitude for remaining six cities in our sample. On the other hand, the average open interest of weather options are mostly similar across all eight cities in our sample. In fact, Las Vegas and Sacramento have the highest level of open interest in weather futures options. However, this could be due to the fact that Las Vegas and Sacramento have roughly half of observations than the rest as each of eight cities in our sample have different starting date when the weather derivatives began trading. Weagley (2019) also documents significant drop in weather derivatives trading activity following the 2008 financial crisis, and hence those cities who had active contracts prior to 2008 will have systematically lower average open interest.

Next, the average level of implied volatility of weather options is surprisingly low. Other than the exception of Cincinnati, who has average of 28% implied volatility, all cities have less then 20% implied volatility. This level is lower than the aggregate stock market which usually have average implied volatility above 20%. Individual equity options or other commodities options contracts traded on CME normally exhibits greater level of implied volatility that can range as high as 50% and above. However, note that weather options have the unique nature that the underlying security is the weather futures contract, in which underlying of the underlying depends on the HDD and CDD level measured from the realized temperature. Since realized temperature will not show such large level of volatility within a short period of time, it is somewhat intuitive to see low level of weather options implied volatility.

To understand the nature of the weather option contracts better, we also compute raw

[12] Open interest and trade volume have drastically expanded since 2019 with the increasing focus of climate change risk with possible demand being driven by using any sort of weather payoff driven contract as a hedging source for weather or climate uncertainty risk.

option returns and delta-hedged option returns. We compute them as follows:

$$R^{Opt}_{i,c,t} = \frac{O_{i,c,t} - O_{i,c,t-1}}{O_{i,c,t-1}} \tag{3.1}$$

$$R^{DH,Opt}_{i,c,t} = \frac{O_{i,c,t} - O_{i,c,t-1}}{O_{i,c,t-1}} - \frac{\Delta_{i,c,t-1}(F_{c,t} - F_{c,t-1})}{O_{i,c,t-1}}, \tag{3.2}$$

where $R^{Opt}_{i,c,t}$ and $R^{DH,Opt}_{i,c,t}$ denote raw and delta-hedged option returns for contract i written on city c on day t, respectively. Returns are computed on trade to trade basis so that $t-1$ corresponds to the last time contract i was traded. $F_{c,t}$ and $O_{i,c,t}$ denote the seasonal strip futures and options prices on trade date t.

Last two rows for each city in Table 1 report the average raw option return and static delta-hedged option return. Other than Sacramento, raw option returns are all negative in average in our sample, indicating that end users who take long positions in these contracts end up losing money in average. Similarly, other than an exception of Chicago, average static delta-hedged option returns are all negative. Delta-hedged option return reduces return due to the movement of the underlying security, weather futures contracts in our case. Therefore, it is a good proxy to tell how much investors are willing to pay in order to take positions in the options market. Anecdotal evidences and studies such as Weagley (2019) suggest that local energy and utility firms who are seeking to hedge their weather exposure are dominating end users taking net long positions in weather derivatives market. Given that weather options contracts are ideal product for such hedging purpose, we assume that the hedgers are the ones taking long positions in the weather options contracts. Therefore, negative sign of average delta-hedged option return is consistent with the interpretation that it is the cost of insuring against the changes in weather uncertainty paid by hedgers to liquidity providers.

Table 3 reports the correlation across eight cities for our three volatility related measures: WRVOL, WIVOL, and WVRP. For the weather option implied volatilities (WIVOL) reported in Panel A, most of them show moderate level of positive correlation with exceptions of Nevada and Texas. These two cities, perhaps due to their geographic location, exhibit negative correlation with other cities that are located in different geographic regions. For the weather futures return volatilities (WRVOL) reported in Panel B, we mostly observe consistent pattern with an exception of Texas which now exhibits more positive correlation with the rest. Lastly, for the weather variance risk premium (WVRP) reported in Panel C, overall magnitude of correlations are more positive than the volatility measures. Although there are couple exceptions where the correlation is negative, but it seems like there is a stronger common factor deriving the WVRP measure across eight cities in our sample.

Lastly, we analyze the weather implied volatility across moneyness dimension. While the majority of the contracts traded in this market are at-the-money (ATM) securities that have monenyness defined by strike price to futures price ratio of 1, we still have subset of observations that are either out-of-the-money (OTM) or in-the-money (ITM) that allow use to plot the implied volatility as a function of moneyness. Figures 1 plots the average implied volatility as a function of moneyness (K/F) across all contracts in all cities in our sample. The shape of the implied volatility curve is similar to the one observed in the equity market, exhibiting "smirk" type of pattern where the OTM options have higher implied volatility than the rest while it flattens out across ATM and ITM options. However, the level of implied volatility does not vary as much as other markets, such as equity index or commodities, that they reside within a region between 14.5% and 17%. Therefore, the weak evidence presented in the figure partially supports the intuition that the weather options market is driven by the hedgers paying for extra premium to take long positions shown by higher WIVOL for OTM options. In Figure 2, we plot the same curve individually for eight cities in our sample. The evidence is now more mixed that we see greater level of heterogeneity in the pattern across eight cities. Some cities such as Chicago, Minnesota, and New York show more conventional volatility "smile" pattern where both in and out of money options are more expensive than the ATM options, while city like Texas even shows monotonically decreasing pattern. Note that we have limited number of observations that are not ATM, and the sample size becomes even smaller if we plot separately for each city, thus the average level estimate in individual figures are subject to imprecision. Overall, the patterns from the implied volatility curve are largely consistent with the other markets, such as equity index, that hedgers pay higher premium to enter the market.

3.2 Determinants of Weather Implied Volatility and Volatility Risk Premium

Having established stylized facts based on the descriptive statistics, we now engage in a more systematic analysis on which economic variables can explain the observed variation of weather implied volatility and volatility risk premium. We consider a set of variables that can be linked to the WIVOL and WVRP in different ways. First, we include variables that measure realizations of weather conditions, such as Storm date and realized temperature. Realizations of extreme weather events increases the variance of realized temperature, and hence should be reflected in the weather implied volatility. Second, we include variables that proxy demand for hedging weather. For this purpose, we use natural logarithm of open interest in Futures and Options contract. Again, this is based on the assumption built upon anecdotal evidences that hedgers take net long positions in the weather derivative market. Third, we include three representative topics, namely Climate Summits, Hurricanes Floods, and Cities, from a daily media climate change concerns index built by Ardia et al. (2023) that measure textual sentiment on various climate concerns. We also include state-level economic policy uncertainty (EPU) from Elkhami, Jo, and Salerno (2023) to test whether the state-level political uncertainty can play a role in determining hedging demand of local firms. Lastly but importantly, we also include intermediary constraint variable following the main findings from Weagley (2019), who argues that intermediary capital constraint is the main driver of the weather derivatives prices. Note that while Weagley (2019) uses 2008 financial crisis as one of the main shocks to the intermediary capital constraint, our sample covers much longer period far beyond 2008 financial crisis.

Table 4 reports the result based on daily panel regressions to understand what can help explain log of weather implied volatility. In all models, we control for moneyness, time-to-maturity, and include contract level fixed effects. First, three topics from daily media climate change concerns index, namely Climate Summits, Hurricane Floods, and Cities, of Ardia et al. (2023) show statistically significant positive explanatory power of the log-implied volatility, consistent with the intuition that higher climate concern leads to a higher price to insure against it. Next, loadings on the aggregate market demand proxied by open interest of futures and options are both positive and statistically significant. Again with the assumption that the hedgers are net long end-users, it shows that heightened demand drives the option prices to be more expensive. Economic policy uncertainty of Baker, Bloom, and Davis (2016) does not seem to be related to the weather option price, as somewhat intuitive. Overall, the daily panel regression lends support to the realized temperature and hedging demand (or sentiment) as two main channels of how option prices are determined.

As a next step, Table 5 reports the result based on monthly panel regressions on determinants of the weather volatility risk premium. We are restricted to the smaller subset of explanatory variables as the frequency is monthly. In all models, we include state and year-quarter fixed effects. Main findings from Weagley (2019) suggests that weather derivatives are heavily dependent on the intermediary capital constraints, hence emphasizing supply side friction as a main channel. Since the WVRP measure represents the price one has to pay in order to have insurance against the weather uncertainty, we expect the intermediary constraint effect to be also present in the WVRP, if not stronger. Consistent with this supply friction channel, intermediary risk factor loads positively with a statistical significance at the 1% level. In other words, it is more expensive to buy insurance to protect against weather uncertainty when the intermediaries, such as hedge funds, experience capital constraint. However, we find that supply channel is not all that matters for the WVRP. Demand side friction proxied by open interest of the options contract loads positively with the statistical significance, indicating that demand pressure is also one of the main determinants of the WVRP, assuming that hedgers take net long positions in the options contract. Alternatively, we also test demand channel by using the local commercial and residential sales of electricity as explanatory variables. Intuitively, when local energy firms are facing increased electricity sales, they feel less need to hedge against future weather uncertainty, and thus the WVRP level decreases as they are not willing to pay higher price to hedge. It is also noteworthy that when two variables of demand friction, options open interest and electricity sales, are included, intermediary constraint factor is significant only at the 10% level, while the demand friction variables still exhibit statistical significance at the 1% level. In summary, we conclude that both supply and demand side frictions are important determinant of the WVRP, with a highlight that demand side frictions seem to play a pivotal role in addition to the existing studies that have focused on the supply side friction only.

4 WVRP and the Local Financial Market

Upon understanding various characteristics of the weather options data, we next test whether the WVRP measure extracted from the seasonal strip weather options prices can in fact explain local financial market outcomes. For this purpose, we empirically test whether the WVRP measure can explain local municipal and corporate bonds, as well as local firm's equity variance risk premium.

4.1 Municipal Bond, Corporate bond, and Equity Data

In order to test our WVRP measure's impact for local economy, we obtain (i) county level municipal bonds of the surrounding city airport for each weather derivatives city location, (ii) corporate bonds of the firms headquartered in surrounding city airport for each weather derivatives city location, and (iii) firm variance risk premia of the firms headquartered in surrounding city airport for each weather derivatives city location.

We obtain municipal bond issuance data (CUSIP, amount outstanding, issuance date, and maturity date) from Bloomberg for all of the municipal bonds issued within 100km of the airports of the eight cities we are considering.[13] Municipal bond level transaction data for each bond CUSIP is obtained from MRSB via WRDS. MRSB contains all municipal bond transactions data (date of transaction, price, yield, and dollar volume traded) from Jan 3, 2005, to June 30, 2022. Therefore, we limit our sample to all municipal bonds that were issued from Jan 3, 2005, to June 30, 2022 for our counties of interest described above. We apply several standard filters to our municipal data set before beginning our analysis. That is, we remove municipal bond trades that have either (i) missing or less than one year to maturity, (ii) yields that are less than zero or greater than 6.65, (iii) missing or zero notional outstanding, or (iv) whose trade price is less than 52 or greater than 138 (in order to minimize the impact of outliers).[14]

Pursuant to our use of section 2, since our weather derivatives are associated with eight particular airport temperatures, we limit out empirical analysis to the city locations listed in COMPUSTAT city and state information.[15] Pirinsky and Wang (2006) find that less than 3% of firms changed corporate headquarters according to COMPUSTAT and Chaney, Sraer, and Thesmar (2012) find that a firm's corporate headquarters is in fact the majority of the company's real-estate holdings. Our equity options data consists of using the 30 day to maturity, equity option delta of 0.5, average call and put implied volatility from the OptionMetrics Volsurface Database.

Table A.3 reports the summary statistics of individual firm stock variance risk premia (Stock VRP), corporate bond credit spreads (along with time to maturity, duration, amount outstanding) for the cities with surrounding weather derivatives. We obtain the correspond-

[13] Each city/airport (county) is: Atlanta (Fulton), Chicago O'Hare (Cook and Delpont), Cincinnati/Northern Kentucky (Hamilton and Boone, Kentucky), Dallas-Fort Worth (Dallas and Tarran), Las Vegas (Clark), Minneapolis-Saint Paul (Hennepin), New York Laguardia (Manhattan, Brooklyn, Bronx, Queens, Nassau), and Sacremento (Sacramento county).

[14] Table A.2 reports the summary statistics of municipal bond issuance information (CUSIP, amount outstanding, issuance date, and maturity date) from Bloomberg for all municipal bonds issued within 100km of the airports of the eight cities we are considering.

[15] In particular our analysis is confined to the cities of New York, Brooklyn, Staten Island, The Bronx, Long Island City, Queens, Fort Worth, Dallas, Atlanta, Chicago and Evanston, Cincinnati, Las Vegas and North Las Vegas, Saint Paul and Minneapolis, and in California: Sacremento, San Jose, Paolo Alto, Mountain View, Fremont Stockton, and Santa Rosa.

ing corporate bonds for the cross-section of firms within the states of our eight cities of interest. Data for corporate bonds is obtained from WRDS corporate bond returns, MFISD. We use the end of the month corporate bond yield. We remove bonds that are convertibles, private placements, rule 144A, financial, asset backed, or defaulted. Additionally, we require that the bonds have trades that are larger than 10,000, traded within months that are consecutive with at most a month of gap, have a time to maturity that is longer than one year yet shorter than 30 years, and whose bond price is more than 5 and less than 1,000. The average individual corporate bond credit spreads is 2% and ranges from 0.11% at the 10^{th} percentile to 4% at the 90^{th} percentile with an average time to maturity of 9.29 years with average duration of 6.17 years. Lastly, we obtain firm-level stock variance risk premia following the standard literature. Consistent with the previously documented findings, the average individual firm stock variance risk premia is close to 0 being 0.01, and ranges from –0.11 at the 10^{th} percentile to 0.12 at the 90^{th} percentile.

Municipal and corporate bond credit spreads are computed using the risk free interest rate yield curve constructed from Liu and Wu (2022) to match remaining time to maturity to the closest month to maturity risk free interest rate.[16] Since the estimated yield curve data of Liu and Wu (2022) only has estimates of risk free interest rates out to 30 years, we drop, however, municipal bonds with time to maturity greater than 30 years which consists less than 5% of our sample.

Climate projections are obtained from the Coupled Model Comparison Project (CMIP) data repository, which contains the model simulated changing temperatures under similar assumptions but surveyed across different modeling groups for heterogeneity in assumptions and implementations. Following Schlenker and Taylor (2021), we use the 5^{th} round CMIP5 archive using predicted climate trends from 2006 to 2019. The data is available daily from NASA NEXGDDP for the weather station located at each city with traded weather derivatives. Following Schlenker and Taylor (2021) again, we use the NASA NEX-GDDP Rep-

[16] We thank the authors of Liu and Wu (2022) for making their risk free interest rate yield curve estimates publicly available on their website Wu (2023).

resentative Concentration Pathway (RCP) 4.5 warming simulation where the global mean temperature increases by $1.8°C$ ($3.2°F$) by the year 2100 by assuming an additional energy flux of 4.5 W per meter square. Using the climate projections we compute the $XDD_{c,t-1}$ the forecasted value of the end of seasonal strip futures contract payoff for county c at time $t-1$.

Firms reveal some differing levels and different types of exposure on climate change via reporting and in company earnings announcement. Sautner et al. (2023) and Sautner et al. (2022) create quarterly firm specific metrics of the relative frequency mentioned of different types of climate exposure from company earnings calls.[17] In our robustness tests, we control for their firm level of climate change exposure (CCExposure), firm risk exposure related to climate change (CCRisk), and future risk opportunities related to climate change (CCOpportunity^{Risk}). Additionally, we also control for the level of economic uncertainty in our regressions measured by the Economic Policy Uncertainty index (EPU$_{t-1}$) from Baker et al. (2022) and State-level Economic Policy Uncertainty (EJS SEPU$_{s,t-1}$) from Elkhami, Jo, and Salerno (2023) for state s at time t, respectively.[18]

4.2 Methodology

We test our weather variance risk premia's impact on municipal bond credit spreads, the local firm's variance risk premia, and the corporate credit spreads of the local firms headquartered in cities where the weather derivatives are traded. Additionally, we test the impact of our weather volatility uncertainty measures (WVOL$_{c,t}$) outlined in Section 2: $\text{WVOL}_{c,t} = \{\text{WRVOL}_{c,t}, \text{WIVOL}_{c,t}, \text{WVRP}_{c,t}\}$.

Following the recommendations of Dell, Jones, and Olken (2015), we measure the impact of all our weather volatility uncertainty measures on credit spreads and firm variance risk premia using a linear panel regression model specification. Given that our research question

[17] We thank the authors for making their measure of firm level climate exposure publicly available on their website Sautner (2023).

[18] We thank the authors for making their state level economic uncertainty measure freely available on their website.

is largely concerned with a contemporaneous impact (and a one month ahead predictive impact), which are short term analysis as oppose to longer term impact of temperature, a linear panel model over non-linear model is considered as an appropriate modelling assumption. Additionally, as per Dell, Jones, and Olken (2015), we show that our results are robust to controlling for a period lag in the dependent variable in an untabulated result.

In order to measure the contemporaneous impact of the weather volatility uncertainty measures on municipal bond credit spreads, we use the following panel regression specification similar to Acharya et al. (2022)

$$\text{Muni. Spread}_{b,c,t} = \gamma_c + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{b,c,t} + \epsilon_{b,c,t}, \tag{4.1}$$

where Muni. $\text{Spread}_{b,c,t}$ is the credit spread during month t of bond b whose issuer is located in county c. Control variables in X include the bond's time to maturity and log of bond turnover. We also include bond and time (year–quarter) fixed effects. Additionally, we control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time t ($XDD_{c,t}$).

Similarly, we measure the contemporaneous impact of the weather volatility uncertainty measures on corporate bond credit spreads, using the following panel regression specification similar to Acharya et al. (2022)

$$\text{Corp. Spread}_{b,c,s,t} = \gamma_s + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{b,s,t} + \epsilon_{b,s,t}, \tag{4.2}$$

where Corp. $\text{Spread}_{b,c,s,t}$ is the credit spread during the month t of bond b where issuing firm s is headquartered near the county c. Control variables and X include the bond's time to maturity, bond credit rating, and log of bond turnover.[19] We also include individual corpo-

[19] The corporate bond credit rating is provided in WRDS Corporate bond returns and takes on a numerical integer values from 1 to 22 where a lower numerical score indicates a higher credit rating such as 1 being AAA. Numerical Credit ratings from 1 to 10 are considered investment grade (AAA to BB-) whereas 11 to 22 (BBB+ and below) are considered high yield or speculative grade.

rate bond and time (year–quarter) fixed effects. Additionally, we control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time t ($XDD_{c,t}$).

Lastly, we measure the contemporaneous impact of our weather volatility uncertainty measures on the individual firm's stock variance risk premia. Building on the panel regression specification from Kruttli, Roth Tran, and Watugala (2023), we estimate the following panel regression

$$\text{Stock VRP}_{s,c,t} = \gamma_s + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{s,t} + \epsilon_{s,t}, \tag{4.3}$$

where Stock VRP$_{s,c,t}$ is the stock variance risk premia during month t of stock s headquartered near county c. We include individual firm and time (year–quarter) fixed effects. Additionally, we control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time t ($XDD_{c,t}$).[20] Lastly, in the predictive panel regressions of the weather volatility uncertainty measures (WVOL$_{c,t}$), we lag by one month all of the variables on the left hand side of each of the three regression equations (4.1), (4.2), and (4.3).

As extensively studied in the context of the equity market, variance risk premium represents the cost of hedging the volatility of the underlying asset. In this view, our weather variance risk premium (WVRP) measure represents the cost of hedging the variation of the local temperature implied from the derivatives market. In fact, it is intuitive to understand the need of hedging local temperature variation as the increased local temperature variation can directly affect municipalities and corporations' cash flow and operating costs. Treating municipalities as a type of firm whose cash flows depend on local activities, we can think both municipalities and corporation's exposure to the weather variation in the context of classical structural model with stochastic asset value volatility as in Du, Elkamhi, and Ericsson (2019) and Goldsmith-Pinkham et al. (2023). In this setup, the underlying asset value of municipality or firm's dynamics features stochastic volatility which its portion is linked to the local

[20]We find similar results when using the $XDD_{c,t}$ as the forecasted value of the end of seasonal strip futures contract payoff instead of payoff uncertainty.

temperature variation. In turn, the risk premium placed on this particular component can be proxied by the observed WVRP from the weather derivatives market. Hence, we expect the price (credit spread) of municipal and corporate bonds to be negatively (positively) related to the level of the WVRP measure, which we confirm empirically in this section.[21]

4.3 Panel Regression Results

We first test the contemporaneous impact of the weather variance risk premia (WVRP) measure on the local financial market variables. For this purpose, we use the cross-section of municipal and corporate bonds credit spreads whose counties and headquarters are in close proximity to those cities with corresponding weather derivatives, respectively. In addition, we also use the firm level variance risk premium as a dependent variable. Table 6 reports the results of estimating equations (4.1) in Panel A, (4.2) in Panel B, and (4.3) in Panel C.

INSERT TABLE 6 HERE

For municipal bonds regression in Panel A, contemporaneous control variables include bond's time to maturity and log of bond turnover. We also control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time t, which we denote by $XDD_{c,t}$.[22] The first column reports the results for the full sample of municipal bonds, while the second and third columns report the panel regression results for the subsets of municipal bonds with time to maturity less and greater than 15 years, respectively. We find that WVRP is positively contemporaneously associated with municipal bond credit spreads with coefficient (t-statistic) of 0.01 (20.17), in line with our expectation. These findings imply that a higher weather variance risk premia is associated with a higher cost of insuring against the changes in the local municipal cash flow uncertainty induced from weather and hence investors demand lower price for municipal bonds since it is more costly to insure, hence

[21] We provide detailed discussion of the model intuition in the Appendix.

[22] All regression estimates include fixed effects for the municipal bond individual CUSIP identifier as well as year–quarter fixed effects.

current municipal credit spreads increase. The result is stronger for municipal bonds with time to maturity less than 15 years as shown in the second column than the ones with time to maturity greater than 15 years, indicating that investors demand a higher municipal bond price discount for higher cost of insurance in the shorter term than longer term. However, the estimated coefficients are still all statistically significant and positive in both cases.

In Panel B, we report the results for corporate credit spreads where we also control for the ratings of individual corporate bonds. The WVRP is again positively contemporaneously associated with corporate bond credit spreads with coefficient (t-statistic) of 0.01 (5.43). Our results show a higher cost of hedging temperature volatility leads to contemporaneously higher localized corporate credit spreads. These findings imply that a higher weather variance risk premia is associated with a higher cost of insuring against the changes in the local firm cash flow uncertainty induced from weather and hence investors demand lower price for corporate bonds since it is more costly to insure hence current corporate credit spreads increase. When split into the subsets based on the time to maturity being less than or greater than 15 years, WVRP has a larger positive coefficients on the impact of corporate bond credit spreads with shorter term to maturity than longer term to maturity. This indicates that investors demand a higher corporate bond price discount for higher cost of insurance in the shorter term than longer term.

Lastly in Panel C, we report the results for stock variance risk premia. We find that the WVRP shows positive statistically significant relationship with the firm level variance risk premia with coefficients (t-statistic) of 0.03 (2.16). In the second and third columns, we report the results of panel regression with the additional controls for the monthly measured state level uncertainty measure of Baker et al. (2022) (EPU_t) and Elkhami, Jo, and Salerno (2023) (EJS $\mathrm{SEPU}_{s,t}$), respectively. Overall, individually adding state level measures of economic uncertainty does not change any of the original results. Our results show a higher cost of hedging temperature volatility leads to a higher current cost of hedging equity volatility uncertainty which imply that a higher weather variance risk premia is associated with a higher cost of insuring against the changes in the local firm stock cash flow uncertainty induced from weather and hence investors demand lower price due to the fact that it is more costly to insure.

5 Robustness Tests

5.1 The Case for Resolution in Uncertainty Main Results

Our weather variance risk premia findings in sections 4.3 across the municipal, corporate, and stock asset classes are consistent with a story of a higher cost of hedging temperature volatility leads to contemporaneously higher localized municipal and corporate credit spreads and then decreasing within a months time. These findings imply that a higher weather variance risk premia is associated with a higher cost of insuring against the changes in the local firm cash flow uncertainty induced from weather and hence investors demand lower price for municipal and corporate bonds since it is more costly to insure hence current municipal and corporate credit spreads increase. In the subsequent month, a higher weather variance risk premia is consistent with investors demand higher price for municipal and corporate bonds as compensation for having costly to insure hence current municipal and corporate credit spreads decrease.

INSERT TABLE 7 HERE

Table 7 reports monthly panel regressions with the dependent variable in Panel A and B being the municipal and corporate bond credit spreads (at time t) regressed on both $\text{WVRP}_{c,t}$ and $\text{WVRP}_{c,t-1}$ for county c at times t and $t-1$, respectively. All municipal and corporate bond control variables are from the time $t-1$. Columns (2), (3), and (4) control for the one period lagged credit spread as well. In both Panel A and B, columns (1) and (2) report the results for the full sample of bonds whereas columns (3) and (4) report the panel regression results for the subsets of bonds with time to maturity less and greater than 15 years, respectively.

In Panel A, we find that the coefficient of $\mathrm{WVRP}_{c,t}$ is positively associated with a higher municipal bond credit spread with coefficient (t-statistic) of 0.01 (14.79) while the coefficient of $\mathrm{WVRP}_{c,t-1}$ is negatively associated with a higher municipal bond credit spread with coefficient (t-statistic) of -0.01 (-21.01), which is consistent with our findings in sections 4.3 for municipal bonds. Similarly in Panel B, we find that the coefficient of $\mathrm{WVRP}_{c,t}$ is positively associated with a higher corporate bond credit spread with coefficient (t-statistic) of 0.01 (10.57) while the coefficient of $\mathrm{WVRP}_{c,t-1}$ is negatively associated with a higher corporate bond credit spread with coefficient (t-statistic) of -0.01 (-16.79) which is consistent with our findings in sections 4.3 for corporate bonds. Column (2) adds a control for the lag one period municipal (corporate) bond credit spread which does not affect the main findings.

In columns (3) and (4) of both Panels A and B report the panel regression results for the subsets of bonds with time to maturity less and greater than 15 years, respectively. In both columns and in both Panels, the coefficient of $\mathrm{WVRP}_{c,t}$ is positively associated with a higher credit spread and the coefficient of $\mathrm{WVRP}_{c,t-1}$ is negatively associated with a higher credit spread. Comparing columns (3) and (4) finds that the impact of coefficients of $\mathrm{WVRP}_{c,t}$ and $\mathrm{WVRP}_{c,t-1}$ are larger in magnitude for bonds with time to maturity less than 15 years (in column (3)) when compared to those that have time to maturity greater than 15 years (in column (4)). The findings for subsets of bonds with time to maturity less and greater than 15 years are consistent with our findings in sections 4.3.

5.2 Corporate Credit Spread Prediction

Lastly, we test whether the WVRP measure can help predicting the next month corporate bond credit spreads by lagging all explanatory variables in the previous panel regression. Moreover, we include the variables from Sautner et al. (2023) who create various measures of the relative frequency from the textual analysis of the earnings call. In particular, we include the firm level of climate change exposure (CCExposure), the firm risk exposure related to climate change (CCRisk) and the future risk opportunities related to climate change (CCOpportunity^{Risk}).

INSERT TABLE 8 HERE

Table 8 reports the results of estimating panel regression equation 4.2. Panel A controls for the monthly economic policy uncertainty measure (EPU$_{s,t-1}$) of Baker et al. (2022) while Panel B controls for for the monthly measured state level uncertainty measure (EJS SEPU$_{s,t-1}$) from Elkhami, Jo, and Salerno (2023). Overall, controlling for the state level measures of economic policy uncertainty does not alter the predictive ability of the weather variance risk premium. In untabulated result, we perform additional tests of equations 4.1 (and 4.2) controlling for the persistence of the municipal and corporate credit spread (i.e. one period lagged credit spread) also do not affect the main results.

6 Conclusion

Despite a developing literature in weather derivatives, temperature changes (and temperature volatility) on asset prices, uncertainty, and variance risk premia, to the best of our knowledge, our paper uniquely contributes to these strands of the literature variance risk premia from options on local temperature futures contracts (the Weather Variance Risk Premia WVRP). Our WVRP measure shows a higher cost of hedging temperature volatility leads to a lower corporate and municipal credit spreads, and individual stock variance risk premia. Our results highlight the importance of the price of weather variance risk in understanding the local financial markets.

Our weather variance risk premia WVRP measure leaves many avenues for potential future research. Of particular interest is the impact of our WVRP on bank loan spreads, number of building contracts, local housing returns, impact on firm supply chains, investor security holdings. However, we leave these avenues for future research exploration.

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Table 1 Seasonal Strips Futures and Options Summary Statistics

	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Atlanta, GA									
Futures Return	1,846	0	0	0.009	−0.445	−0.009	−0.003	0.003	0.009
Futures Open Interest	1,867	834	400	867	1	50	100	1850	2250
Implied Volatility	12,956	0.16	0.16	0.08	3.35	0.08	0.11	0.19	0.21
Delta	12,956	0.07	0	0.36	0.52	−0.33	−0.09	0.21	0.55
Option Open Interest	12,956	968	750	802	1	250	250	1250	2250
Time to Maturity (TTM)	12,956	0.26	0.24	0.15	0.35	0.06	0.13	0.37	0.46
Moneyness (K/F)	12,956	0.99	0.99	0.12	0.15	0.83	0.9	1.08	1.16
Option Return	9,854	0	0	0.345	9.553	−0.263	−0.071	0.063	0.231
DH Option Return	9,854	−0.01	0	0.939	−11.037	−0.102	−0.007	0.015	0.091
Chicago, IL									
Futures Return	1,346	0	0	0.009	0.102	−0.008	−0.003	0.003	0.008
Futures Open Interest	1,363	269	100	391	2	50	50	300	975
Implied Volatility	8,500	0.15	0.12	0.09	1.47	0.06	0.09	0.16	0.3
Delta	8,500	0.04	0	0.39	0.06	−0.37	−0.08	0.17	0.58
Option Open Interest	8,500	958	500	976	2	50	250	1250	2250
Time to Maturity (TTM)	8,500	0.23	0.21	0.14	0.35	0.06	0.12	0.34	0.43
Moneyness (K/F)	8,500	1	0.99	0.13	0.34	0.85	0.91	1.08	1.17
Option Return	6,004	−0.007	0	0.328	2.275	−0.298	−0.083	0.066	0.222
DH Option Return	6,004	0.005	0	0.622	44.122	−0.12	−0.009	0.014	0.077
Cincinnati, OH									
Futures Return	1,809	0	0	0.009	0.221	−0.009	−0.003	0.004	0.01
Futures Open Interest	1,827	197	150	172	2	50	50	300	350
Implied Volatility	3,949	0.28	0.29	0.08	−0.2	0.16	0.24	0.33	0.37
Delta	3,949	0.11	0	0.41	0.14	−0.38	−0.11	0.35	0.72
Option Open Interest	3,949	1149	1000	733	1	250	750	1500	2000
Time to Maturity (TTM)	3,949	0.22	0.22	0.11	0.13	0.07	0.14	0.31	0.37
Moneyness (K/F)	3,949	0.99	0.97	0.17	0.41	0.77	0.87	1.1	1.21
Option Return	3,393	−0.001	0	0.316	4.318	−0.25	−0.091	0.084	0.222
DH Option Return	3,393	−0.007	0	0.239	7.734	−0.104	−0.014	0.016	0.066
Dallas, TX									
Futures Return	1,558	0	0	0.008	0.272	−0.008	−0.003	0.003	0.008
Futures Open Interest	1,573	291	200	306	2	50	100	400	850
Implied Volatility	11,608	0.15	0.15	0.06	0.39	0.09	0.11	0.19	0.23
Delta	11,608	0.05	0	0.37	0.23	−0.36	−0.08	0.19	0.53
Option Open Interest	11,608	899	750	694	1	250	300	1250	2000
Time to Maturity (TTM)	11,608	0.23	0.23	0.13	0.21	0.06	0.13	0.34	0.42
Moneyness (K/F)	11,608	1	1	0.13	0.08	0.84	0.91	1.09	1.17
Option Return	8,615	−0.01	0	0.318	3.821	−0.25	−0.082	0.059	0.2
DH Option Return	8,615	−0.007	0	0.503	−5.38	−0.116	−0.013	0.014	0.079
Las Vegas, NV									
Futures Return	839	0	0	0.006	0.181	−0.006	−0.002	0.003	0.006
Futures Open Interest	849	241	150	194	1	50	100	350	650
Implied Volatility	4,800	0.1	0.07	0.06	2.66	0.04	0.06	0.11	0.18
Delta	4,800	0	0	0.35	0.29	−0.4	−0.08	0.04	0.51
Option Open Interest	4,800	1490	1250	1278	1	250	500	2500	3000
Time to Maturity (TTM)	4,800	0.2	0.19	0.13	0.52	0.04	0.1	0.29	0.37
Moneyness (K/F)	4,800	0.99	0.99	0.09	0.07	0.88	0.94	1.05	1.11
Option Return	2,958	−0.025	0	0.309	0.269	−0.308	−0.125	0.083	0.25
DH Option Return	2,958	−0.016	0	0.2	−1.423	−0.14	−0.013	0.022	0.101
Minneapolis, MN									
Futures Return	1,255	0	0	0.011	0.16	−0.009	−0.003	0.004	0.011
Futures Open Interest	1,270	141	100	91	1	50	50	200	250
Implied Volatility	8,291	0.16	0.13	0.1	1.39	0.07	0.1	0.19	0.33
Delta	8291	0.12	0	0.41	−0.02	−0.34	−0.06	0.37	0.72
Option Open Interest	8,291	849	750	585	1	250	250	1250	1500
Time to Maturity (TTM)	8,291	0.23	0.22	0.14	0.23	0.05	0.12	0.34	0.43
Moneyness (K/F)	8,291	1	0.99	0.11	0.37	0.87	0.92	1.06	1.14
Option Return	6,481	−0.001	0	0.297	4.131	−0.214	−0.067	0.059	0.184
DH Option Return	6,481	−0.001	0	0.817	29.681	−0.062	−0.004	0.008	0.048
New York, NY									
Futures Return	2,396	0	0	0.007	−0.07	−0.007	−0.002	0.002	0.007
Futures Open Interest	2,420	418	350	317	1	50	150	650	905
Implied Volatility	20,596	0.15	0.14	0.06	0.59	0.08	0.11	0.19	0.23
Delta	20,596	0.01	0	0.36	−0.12	−0.4	−0.1	0.17	0.44
Option Open Interest	20,596	1095	750	937	2	250	250	1500	2500
Time to Maturity (TTM)	20,596	0.26	0.26	0.15	0.25	0.07	0.14	0.38	0.47
Moneyness (K/F)	20,596	1	1	0.13	0.13	0.84	0.91	1.09	1.18
Option Return	15,497	−0.001	0	0.364	17.128	−0.248	−0.064	0.048	0.2
DH Option Return	15,497	−0.001	0	0.887	5.908	−0.098	−0.006	0.015	0.087
Sacramento, CA									
Futures Return	739	0	0	0.009	−0.132	−0.01	−0.004	0.005	0.011
Futures Open Interest	748	156	75	129	1	50	50	250	400
Implied Volatility	2,499	0.16	0.16	0.05	0.13	0.09	0.12	0.19	0.22
Delta	2,499	0.15	0.03	0.3	0.86	−0.11	0	0.31	0.61
Option Open Interest	2,499	1380	1000	962	1	250	500	2000	2250
Time to Maturity (TTM)	2,499	0.23	0.21	0.14	0.37	0.06	0.12	0.34	0.44
Moneyness (K/F)	2,499	1.02	1.03	0.15	−0.24	0.78	0.93	1.12	1.21
Option Return	1,689	0.003	0	0.454	5.902	−0.333	−0.12	0.082	0.31
DH Option Return	1,689	−0.002	0	0.312	8.485	−0.146	−0.021	0.028	0.112

Note: This table reports the sample statistics of the implied volatility, option open interest, and remaining time to maturity (in years) for each of the CME Weather derivatives seasonal strip options mentioned in Table A.1.

Table 2 Seasonal Strips Variance Measures Summary Statistics

	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Atlanta, GA									
WVRP	68	0.0416	0.0405	0.0815	0.1834	−0.0811	−0.0099	0.0974	0.1402
WIVOL	69	0.1611	0.1433	0.0841	2.6535	0.079	0.1194	0.1826	0.2427
WRVOL	70	0.1163	0.1096	0.0676	0.5479	0.0294	0.0742	0.151	0.2235
Chicago, IL									
WVRP	59	0.0262	0.0269	0.0653	0.4349	−0.0568	−0.0235	0.0737	0.0996
WIVOL	59	0.1511	0.12	0.0908	1.4863	0.0649	0.0926	0.1765	0.3406
WRVOL	59	0.1249	0.1029	0.0901	1.2561	0.0429	0.0562	0.1523	0.3025
Cincinnati, OH									
WVRP	36	0.0925	0.07	0.1231	−1.4752	0.0116	0.0367	0.1962	0.2614
WIVOL	36	0.2861	0.3	0.0749	−0.1736	0.1879	0.2316	0.3398	0.3779
WRVOL	44	0.1753	0.1706	0.1098	3.1185	0.0653	0.1074	0.2242	0.2479
Dallas, TX									
WVRP	63	0.0505	0.0413	0.0758	0.7341	−0.0123	0.0192	0.0761	0.1437
WIVOL	65	0.1651	0.1511	0.0527	0.7628	0.1049	0.1227	0.1997	0.2431
WRVOL	63	0.1151	0.1014	0.0557	1.0433	0.06	0.0821	0.1402	0.1943
Las Vegas, NV									
WVRP	32	0.025	0.0055	0.0671	1.8094	−0.0267	−0.0057	0.0392	0.0918
WIVOL	33	0.111	0.0845	0.0664	1.6251	0.0547	0.0635	0.169	0.1853
WRVOL	32	0.0867	0.0787	0.0453	0.3418	0.0391	0.06	0.1104	0.1584
Minneapolis, MN									
WVRP	56	0.0559	0.0528	0.0784	0.5868	−0.0314	0.0098	0.0968	0.1425
WIVOL	59	0.1677	0.1383	0.0945	1.4251	0.0748	0.1075	0.1872	0.3373
WRVOL	57	0.1155	0.0815	0.0839	1.2747	0.046	0.0582	0.1261	0.2629
New York, NY									
WVRP	96	0.06	0.0522	0.0724	0.1521	−0.0196	0.0155	0.1013	0.1545
WIVOL	96	0.1615	0.1515	0.0547	0.3614	0.0883	0.1188	0.1998	0.2296
WRVOL	101	0.0983	0.0879	0.0538	0.5593	0.0393	0.0686	0.1182	0.1813
Sacramento, CA									
WVRP	27	0.0022	−0.0104	0.0633	0.9216	−0.0615	−0.0455	0.0425	0.1157
WIVOL	27	0.1581	0.1581	0.0348	0.3535	0.109	0.1347	0.1864	0.1941
WRVOL	28	0.1532	0.1586	0.0567	−0.7521	0.0757	0.1226	0.1973	0.2204

Note: This table reports the sample statistics of the weather seasonal strip futures realized volatility ($\text{WRVOL}_{c,t}$), average option implied volatility ($\text{WIVOL}_{c,t}$), and the weather variance risk premia ($\text{WVRP}_{c,t}$, the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$) for each month t for each city c as outlined in Section 2.

Table 3 : Correlations of Weather Risk Measures between Cities

Panel A: Correlations of WIVOL								
	WIVOL (IL)	WIVOL (NY)	WIVOL (NV)	WIVOL (MN)	WIVOL (GA)	WIVOL (CA)	WIVOL (OH)	WIVOL (TX)
WIVOL (IL)	1	0.4778	−0.4022	0.8362	0.0192	0.4622	0.729	−0.2306
WIVOL (NY)	0.4778	1	−0.5316	0.7138	−0.0524	0.4661	0.4757	−0.1087
WIVOL (NV)	−0.4022	−0.5316	1	−0.3156	0.3973	0.4847	0.1693	0.4066
WIVOL (MN)	0.8362	0.7138	−0.3156	1	0.0204	0.5736	0.6537	−0.1636
WIVOL (GA)	0.0192	−0.0524	0.3973	0.0204	1	0.7743	−0.2398	0.4023
WIVOL (CA)	0.4622	0.4661	0.4847	0.5736	0.7743	1	0.4013	0.5028
WIVOL (OH)	0.729	0.4757	0.1693	0.6537	−0.2398	0.4013	1	0.1789
WIVOL (TX)	−0.2306	−0.1087	0.4066	−0.1636	0.4023	0.5028	0.1789	1
Panel B: Correlations of WRVOL								
	WRVOL (IL)	WRVOL (NY)	WRVOL (NV)	WRVOL (MN)	WRVOL (GA)	WRVOL (CA)	WRVOL (OH)	WRVOL (TX)
WRVOL (IL)	1	0.781	−0.37	0.8811	0.0825	0.2854	0.6132	0.0761
WRVOL (NY)	0.7806	1	−0.0756	0.7187	0.3794	0.4548	0.5001	0.1681
WRVOL (NV)	−0.37	−0.076	1	−0.5281	0.3392	0.6232	0.1454	0.6835
WRVOL (MN)	0.8811	0.719	−0.5281	1	−0.0578	0.765	0.8281	−0.121
WRVOL (GA)	0.0825	0.379	0.3392	−0.0578	1	0.7644	0.6255	0.4441
WRVOL (CA)	0.2854	0.455	0.6232	0.765	0.7644	1	0.8815	−0.0923
WRVOL (OH)	0.6132	0.5	0.1454	0.8281	0.6255	0.8815	1	0.0221
WRVOL (TX)	0.0761	0.168	0.6835	−0.121	0.4441	−0.0923	0.0221	1
Panel C: Correlations of WVRP								
	WVRP (IL)	WVRP (NY)	WVRP (NV)	WVRP (MN)	WVRP (GA)	WVRP (CA)	WVRP (OH)	WVRP (TX)
WVRP (IL)	1	0.2919	0.229	0.513	0.5532	−0.122	−0.1783	0.416
WVRP (NY)	0.2919	1	0.3977	0.5746	0.5665	0.3105	0.374	0.4603
WVRP (NV)	0.229	0.3977	1	0.3813	0.3675	0.7045	0.4297	0.2173
WVRP (MN)	0.513	0.5746	0.3813	1	0.5223	0.2464	0.5276	0.4445
WVRP (GA)	0.5532	0.5665	0.3675	0.5223	1	0.8351	0.3978	0.5048
WVRP (CA)	−0.122	0.3105	0.7045	0.2464	0.8351	1	0.8517	−0.1019
WVRP (OH)	−0.1783	0.374	0.4297	0.5276	0.3978	0.8517	1	0.2972
WVRP (TX)	0.416	0.4603	0.2173	0.4445	0.5048	−0.1019	0.2972	1

Notes: Table contains the between cities correlations of the average option implied volatility ($\text{WIVOL}_{c,t}$) in Panel A, weather seasonal strip futures realized volatility ($\text{WRVOL}_{c,t}$) in Panel B, and the weather variance risk premia ($\text{WVRP}_{c,t}$, the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$) in Panel C. The sample period is monthly observations from January 2006 to December 2019.

Table 4 Determinants of Weather Implied Volatility

	log-implied volatility								
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
storm date	$0.1e-3$	$-0.1e-3$	$-0.1e-3$	$0e-3$	$-0.1e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(0.1)	(-0.04)	(-0.05)	(0.01)	(-0.05)	(-0.01)	(0.04)	(-0.01)	(-0.03)
EPU	$1.1e-3$	$1.7e-3$	$1.5e-3$	$1.9e-3$	$1.2e-3$	$1.4e-3$	$3.2e-3$	$2.3e-3$	$2e-3$
	(0.07)	(0.11)	(0.1)	(0.12)	(0.07)	(0.09)	(0.2)	(0.15)	(0.12)
Temperature (Forecasted)	$0.3e-3$		$-0.1e-3$						
	(0.82)		(-0.32)						
Temperature (realized)		$0.3e-3$	$0.4e-3$	$0.3e-3$	$0.4e-3$	$0.4e-3$	$0.4e-3$	$0.4e-3$	$0.4e-3$
		(1.67)	(2.18)	(1.84)	(1.94)	(2.05)	(2.12)	(1.95)	(1.95)
log(wth Optss OI_t)				0.04		0.03			
				(2.06)		(1.60)			
log(wth Futss OI_t)					0.04	0.04			
					(2.74)	(2.55)			
Climate Summits							0.04		
							(5.77)		
Hurricanes Floods								0.02	
								(3.69)	
Cities									0.02
									(3.54)
moneyness	0.43	0.43	0.43	0.43	0.41	0.41	0.43	0.43	0.43
	(4.17)	(4.28)	(4.15)	(4.26)	(3.95)	(3.96)	(4.22)	(4.25)	(4.24)
TTM	1.09	1.09	1.09	1.1	1.15	1.16	1.09	1.1	1.1
	(25.83)	(26.46)	(25.61)	(25.57)	(22.83)	(22.72)	(25.1)	(25.41)	(25.38)
Contract Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
$R^2(\%)$	66.04	66.04	66.05	66.06	66.1	66.12	66.13	66.08	66.07
N obs	$73,154$	$73,199$	$73,154$	$73,199$	$73,199$	$73,199$	$73,199$	$73,199$	$73,199$

Note: This table reports daily panel regressions with the dependent variable being the log-implied volatility and control for both moneyness and option time to maturity. All regression estimates include option contract specific fixed effects. T-statistics are in parentheses under the coefficients.

Table 5 Determinants of Weather Volatility Risk Premium

	Weather Volatility Risk Premium						
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wth Opt_{ss} OI_t)	0.03				0.03	0.03	0.03
	(3.76)				(4.32)	(4.32)	(4.32)
log(wth Fut_{ss} OI_t)		−0.01			−0.01	−0.011	−0.01
		(−1.27)			(−1.43)	(−1.67)	(−1.43)
EPU (State)			−0.01		−0.01	−0.01	−0.01
			(−0.95)		(−0.95)	(−0.70)	(−0.95)
Inter risk factor2				0.10	0.07	0.09	0.06
				(2.81)	(2.69)	(1.79)	(1.70)
log(commercial sales)						−0.18	
						(−3.77)	
log(residential sales)							−0.13
							(−4.42)
State Fixed Effects	Y	Y	Y	Y	Y	Y	Y
Year–Quarter Fixed Effects	Y	Y	Y	Y	Y	Y	Y
R^2(%)	36.47	35.26	34.79	35.05	37.69	39.55	42.77
N obs	437	437	437	437	437	437	437

Note: All regressions include state, year and quarter fixed effects and standard errors are clustered by state.

Table 6 WVRP and the Local Financial Market

	Panel A: Municipal Bond Credit Spreads			Panel B: Corporate Bond Credit Spreads			Panel C: Stock Variance Risk Premia		
Variable	Full Sample	$TTM < 15$	$TTM > 15$	Full Sample	$TTM < 15$	$TTM > 15$	Full Sample	+EPU	+SEPU
$\text{WVRP}_{c,t}$	0.01	0.01	$4.1e-3$	0.01	0.01	$1.5e-3$	0.03	0.03	0.03
	(20.17)	(26.65)	(7.37)	(5.43)	(3.90)	(1.27)	(2.16)	(2.23)	(2.15)
$XDD_{c,t}$	$0e-3$	$-0e-3$	$0e-3$	-0.00	$-0e-3$	$0e-3$	-0.00	-0.00	-0.00
	(0.62)	(-3.60)	(2.63)	(-0.68)	(-0.93)	(2.33)	(-0.24)	(-0.81)	(-0.22)
$TTM_{b,t}$	$-3.6e-3$	$-3.7e-3$	$-3.4e-3$	$-0.2e-3$	$0.4e-3$	$-2.1e-3$			
	(-15.43)	(-15.22)	(-7.94)	(-0.28)	(0.25)	(-2.04)			
$\log(\text{AmtOut/DollVolume})_{b,t}$	$-0.2e-3$	$-0.3e-3$	$-0.1e-3$	-0.00	$-0.2e-3$	$-0.1e-3$			
	(-13.88)	(-18.81)	(-2.32)	(-0.26)	(-2.06)	(-0.92)			
$Rating_{b,t}$				0.01	0.01	$1.9e-3$			
				(9.38)	(59.97)	(17.39)			
EPU_t								0.01	
								(2.77)	
EJS $\text{SEPU}_{c,t}$									$-0.9e-3$
									(-0.30)
R^2	81.32	85.12	80.78	67.27	67.83	70.51	78.94	74.87	78.94
N obs	62,748	37,056	25,692	56,949	45,089	11,860	21,722	21,722	21,722
Bond CUSIP Fixed Effects	Y	Y	Y	Y	Y	Y			
Firm Fixed Effects							Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: This table reports monthly panel regressions with the dependent variable being the municipal and corporate bond credit spreads, and stock variance risk premia (at time t) regressed on WVRP_t. $\text{WVRP}_{c,t}$ is defined as the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$ for county c at time t. $XDD_{c,t}$ is the forecasted value of the end of the month seasonal strip futures contract payoff for county c at time t. Controls include the remaining time to maturity (TTM, in years) and the $\log(\text{AmtOut/DollVolume})_{i,t}$ which is the log-ratio of the bond outstanding over the amount of dollar traded volume of the bond i at time t. All regression estimates include fixed effects for the bond individual CUSIP identifier as well as year quarter fixed effects. t-statistics are presented in parentheses under the coefficients.

Table 7 Resolution of Uncertainty of Municipal and Corporate Credit Spreads

Panel A: Municipal Credit Spreads				
Variable	(1)	(2)	(3)	(4)
$\text{WVRP}_{c,t}$	0.01	0.01	0.01	$4.2e-3$
	(14.79)	(18.03)	(23.54)	(6.83)
$\text{WVRP}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-21.01)	(-24.65)	(-23.59)	(-11.53)
$XDD_{c,t-1}$	$0e-3$	$-0e-3$	$-0e-3$	$0e-3$
	(0.00)	(-0.89)	(-4.30)	(1.20)
$TTM_{b,t-1}$	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.3e-3$
	(3.55)	(3.59)	(3.62)	(2.09)
$\log(\text{AmtOut/DollVolume})_{b,t-1}$	$-0.1e-3$	$0e-3$	$0e-3$	$0e-3$
	(-4.46)	(-0.55)	(0.57)	(-1.40)
$CS_{b,t-1}$		0.24	0.19	0.21
		(55.64)	(32.20)	(30.68)
R^2	81.37	82.58	85.69	81.57
N obs	52,642	52,642	31,010	21,632
Bond Fixed Effects	Y	Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y

Panel B: Corporate Credit Spreads				
Variable	(1)	(2)	(3)	(4)
$\text{WVRP}_{c,t}$	0.01	0.01	0.01	$4.2e-3$
	(10.57)	(14.28)	(21.42)	(5.37)
$\text{WVRP}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-16.79)	(-19.71)	(-18.15)	(-9.39)
$XDD_{c,t-1}$	0.00	-0.00	-0.00	0.00
	(0.00)	(-0.84)	(-4.48)	(1.14)
$TTM_{b,t-1}$	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.3e-3$
	(2.32)	(2.21)	(2.18)	(1.22)
$\log(\text{AmtOut/DollVolume})_{b,t-1}$	$-0.1e-3$	0.00	0.00	0.00
	(-2.97)	(-0.39)	(0.47)	(-0.93)
$CS_{b,t-1}$		0.24	0.19	0.21
		(15.72)	(8.15)	(10.68)
R^2	83.4	84.47	86.93	83.95
N obs	52,642	52,642	31,010	21,632
Bond Fixed Effects	Y	Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y

Note: This table reports monthly panel regressions with the dependent variable in Panel A (B) being the municipal (corporate) bond credit spreads (at time t) regressed on both $\text{WVRP}_{c,t}$ and $\text{WVRP}_{c,t-1}$ for county c at times t and $t-1$ respectively. All bond control variables are at time $t-1$. Columns (2), (3), and (4) control for the lag one period credit spread. In both Panel A and B, columns (1) and (2) report the results for the full sample of bonds and whereas in columns (3) and (4) report the panel regression results for the subsets of bonds with time to maturity less and greater than 15 years respectively. All regression estimates include bond fixed effects and year quarter fixed effects. t-statistics are in parentheses under the coefficients with standard errors clustered by bond.

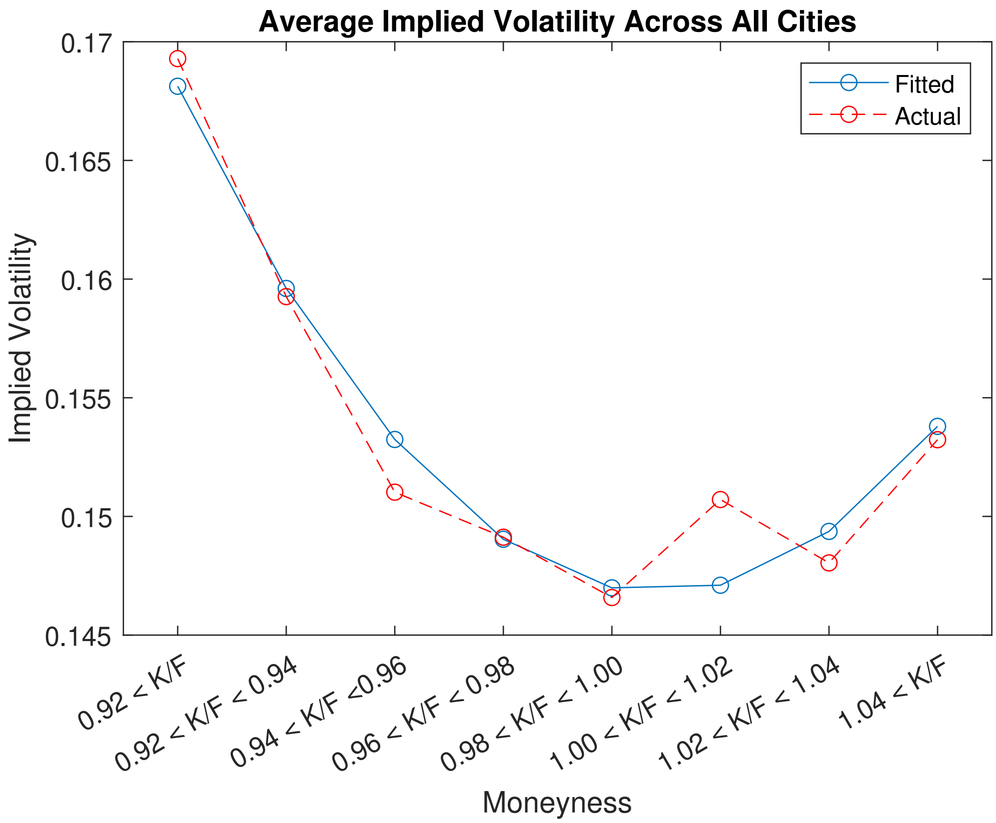
Table 8 Robustness: Corporate Credit Spreads and WVRP (Predictive)

Panel A: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\text{WVRP}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-5.16)	(-5.18)	(-5.24)	(-5.17)
$XDD_{c,t-1}$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-2.61)	(-3.15)	(-3.18)	(-3.14)
$TTM_{b,t-1}$	$0.7e-3$	$1.1e-3$	$1.1e-3$	$1.1e-3$
	(0.00)	(2.48)	(2.48)	(2.45)
$Rating_{b,t-1}$	0.01	0.01	0.01	0.01
	(51.90)	(51.96)	(51.91)	(51.99)
$\log(\text{AmtOut/DollVolume})_{b,t-1}$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.2e-3$
	(-3.32)	(-2.86)	(-2.86)	(-2.84)
EPU_{t-1}	$0.9e-3$	$0.7e-3$	$0.7e-3$	$0.7e-3$
	(3.41)	(2.34)	(2.40)	(2.35)
cc risk $\text{ew}_{s,t-1}$		-1.1		
		(-1.95)		
cc expo $\text{ew}_{s,t-1}$			0.14	
			(1.69)	
op risk $\text{ew}_{s,t-1}$				-3.34
				(-2.21)
R^2	64.85	65.20	65.20	65.20
N obs	56,013	52,999	52,999	52,999
Bond Fixed Effects	Y	Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y

Panel B: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\text{WVRP}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-4.85)	(-4.76)	(-4.84)	(-4.76)
$XDD_{c,t-1}$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-1.79)	(-2.48)	(-2.51)	(-2.46)
$TTM_{b,t-1}$	$0.7e-3$	$1.1e-3$	$1.1e-3$	$1.1e-3$
	(0.00)	(2.58)	(2.58)	(2.56)
$Rating_{b,t-1}$	0.01	0.01	0.01	0.01
	(51.76)	(51.85)	(51.80)	(51.88)
$\log(\text{AmtOut/DollVolume})_{b,t-1}$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(-3.31)	(-2.88)	(-2.87)	(-2.86)
EJS $\text{SEPU}_{c,t-1}$	$-0.5e-3$	$-0.7e-3$	$-0.7e-3$	$-0.7e-3$
	(-1.68)	(-2.56)	(-2.41)	(-2.56)
cc risk $\text{ew}_{s,t-1}$		-1.17		
		(-2.08)		
cc expo $\text{ew}_{s,t-1}$			0.13	
			(1.52)	
op risk $\text{ew}_{s,t-1}$				-3.49
				(-2.32)
R^2	64.84	65.20	65.20	65.20
N obs	56,013	52,999	52,999	52,999
Bond Fixed Effects	Y	Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y

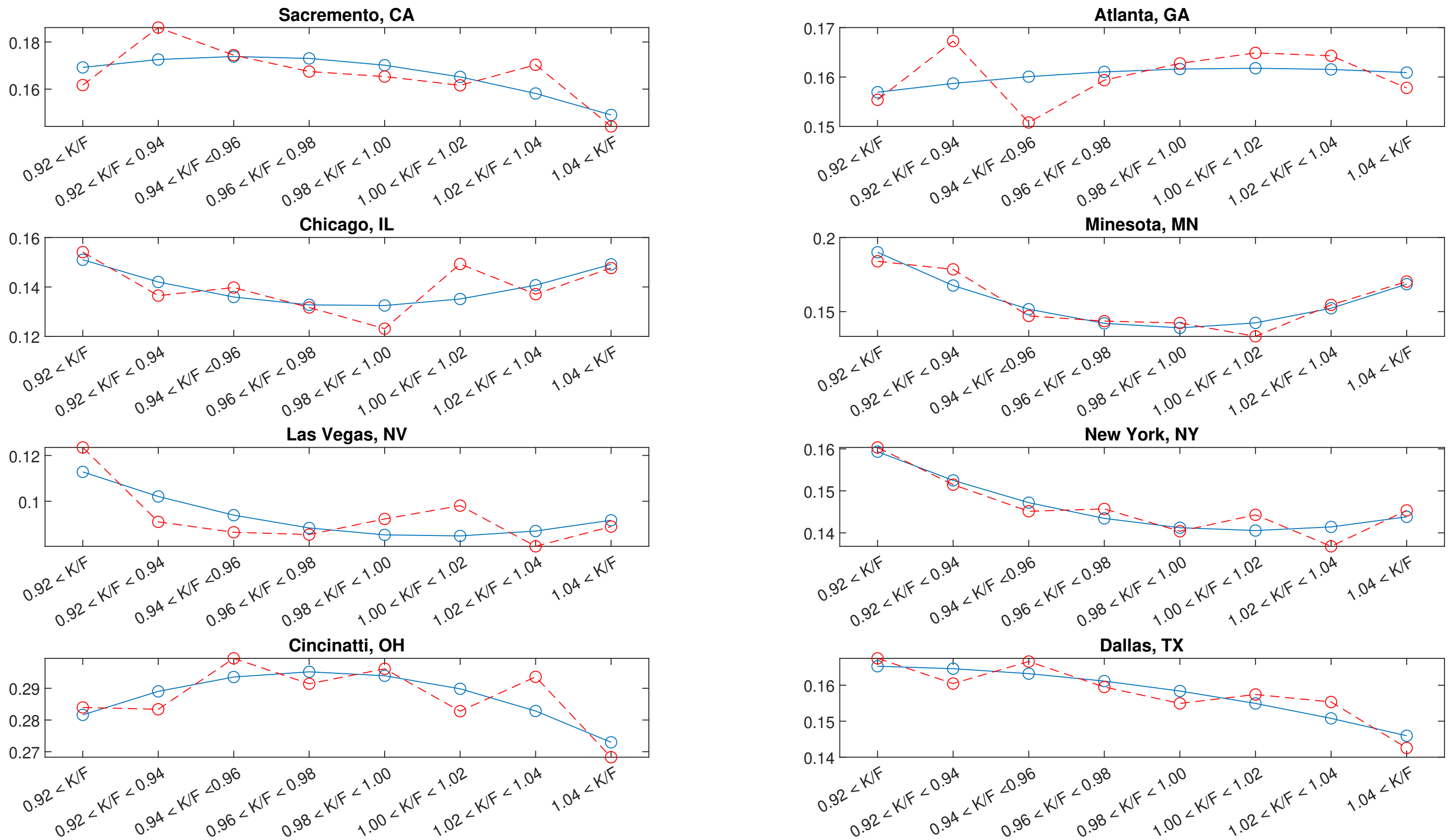
Note: This table reports monthly panel regressions with the dependent variable being the corporate bond credit spreads (at time t) regressed on $t-1$. $\text{WVRP}_{c,t-1}$ is the difference between the $\text{WIVOL}_{c,t-1}$ and $\text{WRVOL}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}$ is the forecasted value of the end of the month seasonal strip futures contract payoff for county c at time $t-1$. Corporate bond controls include the remaining time to maturity (TTM, in years) and the credit rating of bond i at time $t-1$. Panel A reports the results for the full sample of corporate bonds and Panels B and C report the panel regression results for the subsets of corporate bonds with time to maturity less and greater than 15 years respectively. All regression estimates include bond fixed effects and year quarter fixed effects. t-statistics are in parentheses under the coefficients with standard errors clustered by bond.

Fig. 1: Weather Implied Volatility Average across all Eight Cities



Notes: Weather Implied Volatility average across the eight cities. Implied volatility curve is fitted to a polynomial function of moneyness of degree 2. Fitted (actual) implied volatility are shown in blue (red).

Fig. 2: Weather Implied Volatility for each of the Eight Cities



Notes: Weather Implied Volatility for each of the eight cities. Implied volatility curve within each city are fitted to a polynomial function of moneyness of degree 2. Fitted (actual) implied volatility are shown in blue (red).

A Appendix

A.1 Theoretical Motivation

To understand how the weather variance risk premia (WVRP) should be related to the municipal and corporate bond spreads, we largely borrow the framework of Goldsmith-Pinkham et al. (2023) and Du, Elkamhi, and Ericsson (2019), which are based on the classical Merton (1974) model. As in Goldsmith-Pinkham et al. (2023), we view both municipalities and corporation's present value of cash flows can be understood as the asset value X_t in the Merton framework that is assumed to follow a geometric Brownian motion. Furthermore, we follow Du, Elkamhi, and Ericsson (2019) to also allow a stochastic volatility of asset value to incorporate variance risk premium of the asset value. The assumes process for the asset value X_t is thus given by below under the physical measure

$$d\log(X_t) = \mu dt + \sqrt{V_t} dW_t^{\mathbb{P}} \tag{A.1}$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma\sqrt{V_t} dW_t^2. \tag{A.2}$$

Two sources of risk, diffusive and variance risks, are assumed to carry its own risk premia. This leads to the following asset value process under the risk-neutral measure

$$d\log(X_t) = (r - \frac{1}{2}V_t)dt + \sqrt{V_t} dW_t^{\mathbb{Q}} \tag{A.3}$$

$$dV_t = \kappa^*(\theta^* - V_t)dt + \sigma\sqrt{V_t} dW_t^2. \tag{A.4}$$

As in Goldsmith-Pinkham et al. (2023), option-pricing intuition behind the model implies that the bonds will carry higher yields with higher integrated variance V_t over the lifetime under the risk-neutral measure, in which means that higher compensation for variance risk will result in a higher bond yield. We thus link the physical realized volatility of local temperatures to the V_t under the physical measure as it adds uncertainty to the cash flows of municipalities and corporation, while the weather variance risk premium, which is implied premium placed on the weather induced uncertainty by market participants, contributes to the asset variance risk premia in the above model.

In other words, while Goldsmith-Pinkham et al. (2023) distinguishes itself from existing studies by focusing on the effect through asset variance V_t, our main focus is through the variance risk premium channel in the spirit of Du, Elkamhi, and Ericsson (2019). However, the resulting empirical implication is similar that higher level of weather variance risk premium should result in higher yields for municipalities and corporations whose future cash flow uncertainty depends on the local weather conditions.

Table A.1 CME Weather Derivatives Data Details

Options		Futures	
Option Series	CME Code	Futures Series	CME Code
Atlanta HDD NOV Seasonal Strip Options	$11X$	Atlanta HDD NOV Seasonal Strip Futures	$H1X$
Atlanta CDD MAY Seasonal Strip Options	$21K$	Atlanta CDD MAY Seasonal Strip Futures	$K1K$
Chicago HDD NOV Seasonal Strip Options	$12X$	Chicago HDD NOV Seasonal Strip Futures	$H2X$
Chicago CDD MAY Seasonal Strip Options	$22K$	Chicago CDD MAY Seasonal Strip Futures	$K2K$
Cincinnati HDD NOV Seasonal Strip Options	$13X$	Cincinnati HDD NOV Seasonal Strip Futures	$H3X$
Cincinnati CDD MAY Seasonal Strip Options	$23K$	Cincinnati CDD MAY Seasonal Strip Futures	$K3K$
Dallas HDD NOV Seasonal Strip Options	$15X$	Dallas HDD NOV Seasonal Strip Futures	$H5X$
Dallas CDD May Seasonal Strip Options	$25K$	Dallas CDD MAY Seasonal Strip Futures	$K5K$
Las Vegas HDD NOV Seasonal Strip Options	$10X$	Las Vegas HDD NOV Seasonal Strip Futures	$H0X$
Las Vegas CDD MAY Seasonal Strip Options	$20K$	Las Vegas CDD MAY Seasonal Strip Futures	$K0K$
Minneapolis HDD NOV Seasonal Strip Options	$34X$	Minneapolis HDD NOV Seasonal Strip Futures	HQX
Minneapolis CDD MAY Seasonal Strip Options	$44K$	Minneapolis CDD MAY Seasonal Strip Futures	KQK
New York HDD NOV Seasonal Strip Options	$14X$	New York HDD NOV Seasonal Strip Futures	$H4X$
New York CDD MAY Seasonal Strip Options	$24K$	New York CDD MAY Seasonal Strip Futures	$K4K$
Sacremento CDD May Seasonal Strip Options	$45K$	Sacramento CDD MAY Seasonal Strip Futures	KSK
Sacramento HDD NOV Seasonal Strip Options	$35X$	Sacramento HDD NOV Seasonal Strip Futures	HSX

Notes: The first column shows the Chicago Mercantile Exchange (CME) Weather derivatives Options and Futures contracts codes. the options seasonal strip contract is based on the cumulative HDD or CDD values during a five-month period within the season.

Table A.2 Municipal Bonds Summary Statistics

	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
All States									
yield vw	$1,823,869$	0.02	0.02	0.01	0.51	0.01	0.02	0.03	0.04
TTM	$1,823,869$	13.18	12.02	6.93	0.53	4.93	7.7	17.83	23.78
Amt. Out.	$1,823,869$	$56,272,704$	$19,770,000$	$143,147,241$	9.74	$1,465,000$	$5,420,000$	$51,675,000$	$124,145,000$
Muni. CS.	$1,823,869$	$3.4e-3$	$1.7e-3$	0.01	1.19	-0.01	$-2.6e-3$	0.01	0.02
California									
yield vw	$453,909$	0.02	0.02	0.01	0.52	0.01	0.01	0.03	0.04
TTM	$453,909$	12.59	11.28	6.83	0.72	4.79	7.41	16.58	23.41
Amt. Out.	$453,909$	$77,546,286$	$34,675,000$	$212,631,965$	9.24	$3,410,000$	$9,815,000$	$77,840,000$	$134,570,000$
Muni. CS.	$453,909$	$0.7e-3$	$-0.3e-3$	0.01	1.06	-0.01	$-4.1e-3$	$4.1e-3$	0.01
Georgia									
yield vw	$115,270$	0.02	0.02	0.01	0.19	0.01	0.01	0.03	0.04
TTM	$115,270$	12.6	11.39	6.68	0.62	4.84	7.35	16.95	22.52
Amt. Out.	$115,270$	$29,969,859$	$17,025,000$	$55,206,325$	5.72	$2,160,000$	$5,000,000$	$32,510,000$	$58,420,000$
Muni. CS.	$115,270$	$1.5e-3$	$0.7e-3$	0.01	0.5	-0.01	$-3.2e-3$	0.01	0.01
Illinois									
yield vw	$304,445$	0.03	0.03	0.02	0.17	0.01	0.02	0.04	0.06
TTM	$304,445$	13.63	12.94	6.8	0.36	5.11	8.11	18.59	23.32
Amt. Out.	$304,445$	$63,057,899$	$15,000,000$	$128,033,437$	3.58	$1,030,000$	$3,450,000$	$51,365,000$	$169,505,000$
Muni. CS.	$304,445$	0.01	0.01	0.01	0.54	$-2.3e-3$	$2.1e-3$	0.02	0.03
Minnesota									
yield vw	$44,571$	0.02	0.02	0.01	0.36	0.01	0.01	0.03	0.03
TTM	$44,571$	10.67	9.66	5.65	0.89	4.2	6.49	13.98	18.19
Amt. Out.	$44,571$	$7,274,898$	$3,130,000$	$11,316,216$	2.6	$365,000$	$995,000$	$7,370,000$	$19,985,000$
Muni. CS.	$44,571$	$1.8e-3$	$0.6e-3$	0.01	1.66	$-5e-3$	$-2.6e-3$	$4.6e-3$	0.01
New York									
yield vw	$638,503$	0.02	0.02	0.01	0.2	0.01	0.02	0.03	0.04
TTM	$638,503$	14.05	13.1	7.17	0.36	5.18	8.27	19.33	24.78
Amt. Out.	$638,503$	$63,082,161$	$27,965,000$	$124,455,150$	6.16	$3,630,000$	$12,020,000$	$59,775,000$	$150,000,000$
Muni. CS.	$638,503$	$2.6e-3$	$1.5e-3$	0.01	0.92	-0.01	$-2.8e-3$	0.01	0.01
Ohio									
yield vw	$43,532$	0.02	0.02	0.01	0.14	0.01	0.02	0.03	0.04
TTM	$43,532$	12.49	11.05	6.81	0.69	4.75	7.2	16.85	23.05
Amt. Out.	$43,532$	$9,523,498$	$4,750,000$	$16,527,041$	5.09	$680,000$	$1,635,000$	$10,000,000$	$21,120,000$
Muni. CS.	$43,532$	$2.9e-3$	$2.2e-3$	0.01	0.58	$-4.8e-3$	$-1.8e-3$	0.01	0.01
Texas									
yield vw	$223,639$	0.02	0.02	0.01	0.21	0.01	0.01	0.03	0.04
TTM	$223,639$	12.19	10.88	6.63	0.73	4.65	7.1	16.24	22.18
Amt. Out.	$223,639$	$16,838,841$	$4,415,000$	$56,852,062$	8.25	$630,000$	$1,495,000$	$13,470,000$	$28,905,000$
Muni. CS.	$223,639$	$1.9e-3$	$1.2e-3$	0.01	1.09	$-4.8e-3$	$-2.2e-3$	0.01	0.01

Note: This table reports the summary statistics of municipal bond issuance information (CUSIP, amount outstanding, issuance date, and maturity date) from Bloomberg for all of the municipal bonds issued within 100km of the airports of the eight cities we are considering. Each city/airport (county) is: Atlanta (Fulton), Chicago O'Hare (Cook and Delpont), Cincinnati/Northern Kentucky (Hamilton and Boone, Kentucky), Dallas-Fort Worth (Dallas and Tarran), Las Vegas (Clark), Minneapolis-Saint Paul (Hennepin), New York Laguardia (Manhattan, Brooklyn, Bronx, Queens, Nassau), and Sacremento (Sacramento county). Municipal bond remaining time to maturity (TTM, in years).

Table A.3 Stock, Option, Corporate Bond, Balance Sheet Summary Statistics

Variable	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
skewness	229,367	0.06	0.05	0.07	2.72	0.02	0.03	0.08	0.12
stock VRP	184,602	0.01	0.01	0.17	−0.75	−0.11	−0.04	0.05	0.12
EDF	329,828	0.08	$0e-3$	0.2	3.12	$0e-3$	$0e-3$	0.01	0.26
Asset Volatility (EDF)	331,018	0.48	0.39	0.34	2.69	0.19	0.26	0.59	0.9
WRVOL	75,192	0.1	0.09	0.06	1.12	0.04	0.06	0.12	0.18
WIVOL	105,636	0.44	0.4	0.2	0.57	0.18	0.29	0.58	0.74
WVRP	51,981	0.29	0.27	0.22	0.67	0.04	0.09	0.4	0.61
sum CDDi	135,488	290.77	269.19	184.87	0.46	55.18	140.96	426.55	533.54
sum HDDi	135,622	522.37	462.37	327.87	0.77	153.32	270.41	711.04	986.21
sum XDDi	263,247	2585.98	2190.11	1517.41	1.19	1056.95	1600.45	3197.16	4880.6
Corp Bond Ret (EOM)	417,123	0.01	$4.1e-3$	0.04	3.61	−0.02	$-4.2e-3$	0.02	0.03
CORP TMT	417,123	9.29	6.21	8.17	1.19	1.9	3.34	11.92	24.31
DURATION	415,978	6.17	5.07	4.05	0.91	1.81	3.01	8.22	12.71
Corp Bond Ret (L5M)	324,156	0.01	$3.8e-3$	0.03	3.79	−0.02	$-3.7e-3$	0.01	0.03
Corp Rating	396,681	7.92	7.00	3.16	0.96	5.00	6.00	9.00	13.00
Corp Bid Ask Spread	374,208	0.01	$4.1e-3$	0.01	30.81	$1.1e-3$	$2.2e-3$	0.01	0.01
Corp CS	268,652	0.02	0.01	0.03	9.9	$3.1e-3$	0.01	0.02	0.04
Corp Amount Out.	417,105	593,031	400,000	657,336	2.94	40,000	200,000	750,000	1,299,750

Note: This table reports the summary statistics of individual firm stock variance risk premia (Stock VRP), corporate bond credit spreads, corporate bond time to maturity (TTM) from CRSP, OptionMetrics VolSurface, and WRDS Corporate Bond Returns respectively. we limit out empirical analysis to the city locations listed in COMPUSTAT city and state information. In particular our analyis is confined to the cities of New York, Brooklyn, Staten Island, The Bronx, Long Island City, Queens, Fort Worth, Dallas, Atlanta, Chicago and Evanston, Cincinnati, Las Vegas and North Las Vegas, Saint Paul and Minneapolis, and in California: Sacremento, San Jose, Paolo Alto, Mountain View, Fremont Stockton, and Santa Rosa. WRVOL is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly, WIVOL is the weather seasonal strip options monthly average option implied volatility for county c at time t and WVRP is the difference between the WIVOL and WRVOL for county c at time t.

Table A.4 : Correlations

	Correlations										
Variable Names	$WRVOL$	$WVRP$	XDD	CS	TMT	$RATING$	$log(AO/Vol)$	EPU	$log(OIss)$	$log(optOIss)$	$SEPU$
WRVOL	1.00	−0.47	−0.13	−0.02	0.01	0.00	−0.01	−0.01	0.14	0.12	−0.11
WVRP	−0.47	1.00	0.27	0.06	0.01	0.07	0.02	0.2	−0.51	0.15	0.2
XDD	−0.13	0.27	1.00	0.01	0.01	−0.01	0.01	0.21	−0.22	0.25	0.1
CS	−0.02	0.06	0.01	1.00	−0.02	0.4	−0.03	0.16	0.07	0.05	0.12
TMT	0.01	0.01	0.01	−0.02	1.00	−0.03	0.11	−0.02	−0.04	0.00	0.00
RATING	0.00	0.07	−0.01	0.4	−0.03	1.00	−0.12	−0.06	−0.13	−0.04	0.02
log(AO/Vol)	−0.01	0.02	0.01	−0.03	0.11	−0.12	1.00	−0.02	0.00	−0.04	−0.03
EPU	−0.01	0.2	0.21	0.16	−0.02	−0.06	−0.02	1.00	0.1	0.1	0.42
log(OIss)	0.14	−0.51	−0.22	0.07	−0.04	−0.13	0.00	0.1	1.00	−0.17	−0.11
log(optOIss)	0.12	0.15	0.25	0.05	0.00	−0.04	−0.04	0.1	−0.17	1.00	0.05
SEPU	−0.11	0.2	0.1	0.12	0.00	0.02	−0.03	0.42	−0.11	0.05	1.00

Notes: Table contains pooled correlations between the weather derivatives measures from Table A.3. The sample period is monthly observations from January 2006 to December 2019.