Weather Variance Risk Premia*

Joon Woo Bae† Yoontae Jeon‡ Stephen Szaura§ Virgilio Zurita¶

August 29, 2024

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

---

*We acknowledge helpful comments from seminar participants at Case Western Reserve University, McMaster University, BI Norwegian Business School, Oxford University Man Institute, Queen Mary University of London, and the Conference on Climate and Energy Finance, Eastern Finance Association 2024, Western Finance Association 2024, Future of Finance and Information 2024, as well as Patrick Augustin, Dong-Jie Fang (Discussant), Stefano Giglio, Michael Goldstein, Julien Thavard (Discussant), Grigory Vilkov (Discussant), and Sumudu Watugala. We acknowledge financial support from the Social Sciences and Humanities Research Council of Canada Insight Development Grant number 430-2020-00512.

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

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 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

[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 Froote (2001), Cummins, Lalonde, and Phillips (2004), Froote and O Connell (2008), Garmaise and Moskowitz (2009), and Tomunen (2023) amongst others.

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 study different forms of hedging and to understand variance risk across various asset classes.[9]

[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%.

[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

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 and empirical measurement framework, Section 3 presents the main findings, Section 4 provides several robustness checks, and Section 5 concludes.

2 Data and Methodology

2.1 Weather Derivatives 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 season which runs from November through March. Correspondingly, the CDD contracts are

(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.

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

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

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 $\mathrm{HDD}_{i,t}$ ($\mathrm{CDD}_{i,t}$) 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 $20 \times \mathrm{HDD}_{i,t}$ ($20 \times \mathrm{CDD}_{i,t}$). 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. Weather futures options have been used in cross-sectional analysis in Perez-Gonzalez and Yun (2013), Purnanandam and Weagley (2016), and Weagley (2019). However, these papers have used

U.S. monthly weather futures and options, not the seasonal strips. Our dataset includes both monthly futures and seasonal strips to cover comprehensive market landscape in comparison. 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 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

We then obtain daily prices of seasonal strip weather futures contracts from Schlenker and

Taylor (2021) for the following cities/state (airports): 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).[11] The seasonal strip futures data set spans from January 2006 to December 2019. We compute average daily 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 daily 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 ($\text{WRVOL}_{c,t}$ 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 ($\text{WIVOL}_{c,t}$) 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 vari-

[11]We thank the authors of Schlenker and Taylor (2021) for making their replication code publicly available on their website: Taylor (2021).

ance risk premia ($\mathrm{WVRP}_{c,t}$), for each month t for each city c as the difference between the $\mathrm{WIVOL}_{c,t}$ and $\mathrm{WRVOL}_{c,t}$,

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

INSERT TABLE 2 HERE

Table 2 reports the weather seasonal strip variance risk premia, $\mathrm{WVRP}_{c,t}$, as well as $\mathrm{WIVOL}_{c,t}$ and $\mathrm{WRVOL}_{c,t}$ 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).

2.1.1 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.[12] 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

[12]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).

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).[13]

Pursuant to our use of section 2.1, 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.[14] 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.4 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 corresponding 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

[13] Table A.3 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.

[14] 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.

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.[15] 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 Representative 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

[15] 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).

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.[16] 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 $\text{SEPU}_{s,t-1}$) from Elkhami, Jo, and Salerno (2023) for state s at time t, respectively.[17]

2.2 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 citites where the weather derivatives are traded. Additionally, we test the impact of our weather volatility uncertainty measures ($\text{WVOL}_{c,t}$) outlined in Section 2.1: $\text{WVOL}_{c,t} = \{\text{WRVOL}_{c,t}, \text{WIVOL}_{c,t}, \text{WVRP}_{c,t}\}$.

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 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

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

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

measures on municipal bond credit spreads, we use the following panel regression specification similar to Acharya et al. (2022)

$$\text{Muni. Spread}_{b,c,t} = \gamma_c + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{b,c,t} + \epsilon_{b,c,t}, \tag{2.4}$$

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)

$$\text{Corp. Spread}_{b,c,s,t} = \gamma_s + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{b,s,t} + \epsilon_{b,s,t}, \tag{2.5}$$

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 in Z and X include the bond's time to maturity, bond credit rating, and log of bond turnover.[18] We also include individual corporate 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

[18] 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.

regression

$$\text{Stock VRP}_{s,c,t} = \gamma_s + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{s,t} + \epsilon_{s,t}, \tag{2.6}$$

where Stock $\text{VRP}_{s,c,t}$ 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 ($XDD_{c,t}$).[19] Lastly, in the predictive panel regressions of the weather volatility uncertainty measures ($\text{WVOL}_{c,t}$), we lag by one month all of the variables on the left hand side of each of the three regression equations (2.4), (2.5), and (2.6).

3 Main Results

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 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

[19] 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.

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.[20]

3.1 Contemporaneous Results

3.1.1 Municipal Bond Main Results

We test the contemporaneous impact of the four weather volatility uncertainty measures (WVOL) on the cross-section of municipal bonds credit spreads whose counties are in close proximity to those cities with corresponding weather derivatives. Table 3 reports the results of estimating equation 2.4 where the dependent variable is the municipal bond credit spreads. It is regressed individually and contemporaneously on each of the three weather volatility uncertainty measures displayed in columns (1) to (3), respectively, with contemporaneous control variables including bond's time to maturity and log of bond turnover. Note that the regressions in Columns (1) to (3) also control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time t (i.e. $XDD_{c,t}$).[21] Panel A reports the results for the full sample of municipal bonds, and Panels B and C report the panel regression results for the subsets of municipal bonds with time to maturity less and greater than 15 years, respectively.

INSERT TABLE 3 HERE

Panel A of Table 3 shows that WIVOL and WRVOL are all negatively contemporaneously associated with credit spreads, hence a higher temperature futures volatility is associated with a decreasing credit spread (higher bond price) for seasonal strip contracts with coefficients (t-statistic) of $-1e-3$ (-2.09) and -0.01 (-29.03), respectively. Our main interest, 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

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

[21] All regression estimates include fixed effects for the municipal bond individual CUSIP identifier as well as year–quarter fixed effects. t-statistics are presented in parentheses under the coefficient estimates.

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 current municipal credit spreads increase.

Table 3 Panel B (C) respectively re-estimates the monthly panel regression equation 2.4 for the subsets of municipal bonds with time to maturity less (greater) than 15 years. In both panels B and C, WRVOL (WVRP) is negatively (positively) contemporaneously associated with municipal bond credit spreads as in the main results in Panel A. In particular, WVRP has a larger positive coefficients on the impact of municipal bond credit spreads with shorter term to maturity than longer term to maturity indicating that investors demand a higher municipal bond price discount for higher cost of insurance in the shorter term than longer term.

3.1.2 Corporate Bond Main Results

Table 4 reports the results of the estimation of equation 2.5 with the dependent variable being the corporate bond credit spreads regressed individually on each of the three weather volatility uncertainty measures displayed in columns (1) to (3), respectively. As in the municipal bond regressions, all control variables (bond's time to maturity, credit rating, log of bond turnover, and $XDD_{c,t}$) are contemporaneous.[22] 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.

INSERT TABLE 4 HERE

Panel A of Table 4 shows that WIVOL and WRVOL are both negatively contemporaneously associated with corporate credit spreads, hence a higher temperature futures volatility

[22] All regression estimates include fixed effects for the corporate bond and year quarter fixed effects. t-statistics are in parentheses and standard errors are computed by clustering at the corporate bond level. Regressions in Columns (1) to (3) control for the forecasted value of the end of seasonal strip futures contract payoff.

is associated with a decreasing credit spread for monthly and seasonal contracts with coefficients (t-statistic) of -0.01 (-4.16) and -0.01 (-7.30), respectively. 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.

Table 4 Panel B (C), respectively, re-estimates the monthly panel regression equation 2.5 for the subsets of corporate bonds with time to maturity less (greater) than 15 years. In both panels B and C, WIVOL and WRVOL (WVRP) are negatively (positively) contemporaneously associated with corporate bond credit spreads as in the main results in Panel A. In particular, WVRP has a larger positive coefficients on the impact of corporate bond credit spreads with shorter term to maturity than longer term to maturity indicating that investors demand a higher corporate bond price discount for higher cost of insurance in the shorter term than longer term.

3.1.3 Stock VRP Main Results

Table 5 reports the results of the estimation of equation 2.6 with the dependent variable being the firm level variance risk premium regressed individually on each of the three weather volatility uncertainty measures displayed in columns (1) to (3) respectively.[23]

INSERT TABLE 5 HERE

We first find that WIVOL and WRVOL do not show statistically significant relationship contemporaneously with the firm level variance risk premium, with coefficients (t-statistic)

[23] All regression estimates include fixed effects for the firm and year–quarter fixed effects. t-statistics are in parentheses and standard errors are computed by clustering at the firm level. Regressions in Columns (1) to (3) control for the forecasted value of the end of seasonal strip futures contract payoff.

of 0.01 (0.23) and −0.01 (−0.61), respectively. On the other hand, WVRP shows positive statistically significant relationship with the firm level variance risk premia with coefficients (t-statistic) of 0.03 (2.16). Table 5 panels B and C shows the results of panel regression equation 2.6 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 $\text{SEPU}_{s,t}$), respectively. Overall, individually adding state level measures of economic uncertainty does not change any of the original results of Panel A Table 5. 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.

3.2 Predictive Results

3.2.1 Municipal Bond Main Results

We next test the impact of the three weather volatility uncertainty measures (WVOL) and their predictive impact on the cross-section of municipal bonds whose counties are in close proximity to those cities with corresponding weather derivatives. Table 6 displays the results of the estimation of the predictive regression version of equation 2.4 with the dependent variable being the municipal bond credit spreads regressed individually on each of the three weather volatility uncertainty measures displayed in columns (1) to (3) respectively. Each of three weather volatility uncertainty measures (WVOL) are one month prior to the municipal bond credit spreads in order to account for the timing of the data becoming available. Additionally all control variables (bond's time to maturity, log of bond turnover and $XDD_{c,t-1}$) are lagged by one time period.[24]

[24]All regression estimates include fixed effects for the municipal bond individual CUSIP identifier as well as year quarter fixed effects. t-statistics are presented in parentheses under the coefficient estimates.

INSERT TABLE 6 HERE

Table 6 Panel A finds that while WIVOL negatively predicts future municipal credit spreads with a coefficient (t-statistic) of $-4e-3$ (6.94), WRVOL positively predicts future municipal credit spreads with a coefficient (t-statistic) of 0.01 (12.39). Dissecting the source of negative predictability from the WIVOL further, it is coming from the strong negative predictability of WVRP with a coefficient (t-statistic) of -0.01 (-18.13). Hence, hedging a higher temperature futures volatility is associated with a decreasing expected future municipal bond credit spread (i.e. higher expected future municipal bond price) as indicated by the negative weather variance risk premia.

Table 6 Panel B and c re-estimates the monthly predictive panel regression version of equation 2.4 for the subsets of municipal bonds with time to maturity less and greater than 15 years, respectively. In both Panels B and C, We find consistent estimates with the full sample case in Panel A, hence confirming the result is unaffected by the time to maturity of the municipal bonds.

3.2.2 Corporate Bond Main Results

Table 7 displays the results of the predictive regression version of equation 2.5 with the dependent variable being the corporate bond credit spreads regressed individually on each of the three weather volatility uncertainty measures displayed in columns (1) to (3), respectively. Each of the three weather volatility uncertainty measures (WVOL) are one month prior to the corporate bond credit spreads in order to account for the timing of the data becoming available. As in the municipal bond regressions, all control variables (bond's time to maturity, credit rating, log of bond turnover, and $XDD_{c,t-1}$) are lagged by one month period.[25]

INSERT TABLE 7 HERE

[25] All regression estimates include fixed effects for the corporate bond and year quarter fixed effects. t-statistics are in parentheses and standard errors are computed by clustering at the corporate bond level.

Table 7 Panel A reports the result using entire sample. First, WRVOL shows statistically insignificant negative predictive relationship with the corporate credit spread with a coefficient (t-statistic) of $-0.2e-3$ (-0.16). On the other hand, WIVOL strong statistically significant negative predictive relationship with the corporate credit spread with a coefficient (t-statistic) of -0.01 (-6.61), which translates to the finding that the entire predictability is attributable to the difference between the two, the weather variance risk premia. Consequently, WVRP exhibits strong statistically significant negative predictive relationship with the corporate credit spread with a coefficient (t-statistic) of -0.01 (-7.29). Table 7 Panel B and C re-estimates monthly predictive panel regression version of equation 2.5 (shown in Panel A) for the subsets of corporate bonds with time to maturity less and greater than 15 years, respectively. We find consistent estimates with the full sample case in Panel A, hence confirming the result is unaffected by the time to maturity of the corporate bonds.

3.2.3 Stock VRP Main Results

Table 8 displays the results of the estimation of equation 2.6 with the dependent variable being the firm level stock variance risk premium regressed individually on each of the three weather volatility uncertainty measures displayed in columns (1) to (3), respectively.

We find that while the WRVOL shows statistically significant positive predictive relationship with future firm level variance risk premia with a coefficient (t-statistic) of 0.04 (4.08), WIVOL shows statistically insignificant negative predictive relationship with future firm level variance risk premia with a coefficient (t-statistic) of -0.02 (-1.16). Similar to the case of the corporate credit spread case before, this is reconciled by the finding that WVRP carries statistically significant negative predictive relationship with future firm level variance risk premia with a coefficient (t-statistic) of -0.05 (-5.07).

INSERT TABLE 8 HERE

Table 8 panels B and C shows the results of monthly predictive panel regression version of equation 2.6 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 $\text{SEPU}_{s,t}$) respectively. We confirm that individually adding state level measures of economic uncertainty does not change any of the predictive ability of the weather variance measures original results of Table 8.

4 Robustness Tests

4.1 The Case for Resolution in Uncertainty Main Results

Our weather variance risk premia findings in sections 3.1 and 3.2 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 9 HERE

Table 9 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 $\text{WVRP}_{c,t}$ is positively associated with a higher municipal bond credit spread with coefficient (t-statistic) of 0.01 (14.79) while the coefficient of $\text{WVRP}_{c,t-1}$ 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 3.1 and 3.2 for municipal bonds. Similarly in Panel B, we find that the coefficient of $\text{WVRP}_{c,t}$ is positively associated with a higher corporate bond credit spread with coefficient (t-statistic) of 0.01 (10.57) while the coefficient of $\text{WVRP}_{c,t-1}$ 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 3.1 and 3.2 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 $\text{WVRP}_{c,t}$ is positively associated with a higher credit spread and the coefficient of $\text{WVRP}_{c,t-1}$ is negatively associated with a higher credit spread. Comparing columns (3) and (4) finds that the impact of coefficients of $\text{WVRP}_{c,t}$ and $\text{WVRP}_{c,t-1}$ 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 3.1 and 3.2.

4.2 Other Robustness Tests

Firms reveal some of their exposure to climate change via earnings call. Sautner et al. (2023) create various measures of the relative frequency. In particular we control for 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}). Table 10 (panels A, B, and C) presents the results of panel regression equation 2.6 estimation when controlling for the three different measures of climate change exposure. Individually adding the measures of climate change exposure does not alter findings of the original results of Table 8.

INSERT TABLE 10 HERE

Table 11 Panels A and B show the results of estimating panel regression equation 2.5 with the additional controls for $\text{EPU}_{s,t-1}$ and EJS $\text{SEPU}_{s,t-1}$ (monthly measured state level uncertainty measure of Baker et al. (2022) and Elkhami, Jo, and Salerno (2023), respectively) for the state s at time $t-1$, respectively. Overall, controlling for the state level measures of economic policy uncertainty does not alter the predictive ability of the weather variance measures from the original results in Table 7.

INSERT TABLE 11 HERE

Table 11 Panel B presents the results of panel regression equation 2.5 estimation when controlling for the three different measures of climate change exposure. Individually adding the measures of climate change exposure again does not affect the original findings of the Table 7. In untabulated result, we perform additional tests of equations 2.4 (and 2.5) 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.

5 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.

References

Acharya, V., T. Johnson, S. Sundaresan, and T. Tomunen. 2022. Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress. *Working Paper* 1:1–54.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea. 2020. Temperature shocks and establishment sales. *Review of Financial Studies* 33:1331–66.

———. 2023. Temperature Shocks and Industry Earnings News. *Journal of Financial Economics* 150:1–45.

Alekseev, M., S. Giglio, Q. Maingi, J. Selgrad, and J. Stroebel. 2022. A Quantity-Based Approach to Constructing Climate Risk Hedge Portfolios. *NBER Working Paper* 1:1–54.

Armstrong, C. S., A. S. Glaeser, and S. Huang. 2022. Contracting with Controllable Risk. *The Accounting Review* 97:27–50.

Auh, J. K., J. Choi, T. Deryugina, and T. Park. 2023. Natural Disasters and Municipal Bonds. *Working Paper* 1:1–45.

Bae, J. W., Y. Jeon, S. Szaura, and V. Zurita. 2023. Blame it on the weather: Market implied weather volatility and firm performance. *Working Paper* 1:1–41.

Baker, S. R., N. Bloom, and S. Davis. 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131:1593–636.

Baker, S. R., N. Bloom, S. Davis, and J. A. Levy. 2022. State-level economic policy uncertainty. *Journal of Monetary Economics* 132:81–99.

Baker, S. R., N. Bloom, and J. Terry. 2023. Using disasters to estimate the impact of uncertainty. *Review of Economic Studies* 0:1–39.

Bakshi, G. S., and N. Kapadia. 2003. Delta-Hedged Gains and the Negative Market Volatility Risk Premium. *Review of Financial Studies* 16:527–63.

Baldauf, M., L. Garlappi, and C. Yannelis. 2020. Does Climate Change Affect Real Estate Prices? Only if You Believe In It. *Review of Financial Studies* 33:1256–95.

Bali, T. G., S. J. Brown, and Y. Tang. 2017. Is economic uncertainty priced in the crosssection of stock returns? *Journal of Financial Economics* 126:471—489.

Bali, T. G., A. Subrahmanyam, and Y. Wen. 2021. The macroeconomic uncertainty premium in the corporate bond market. *Journal of Financial Economics* 56:1653—1678.

Balsamo, E., and A. Krema. 2023. CME Group Weather Suite Expanded. *Chicago Mercantile Exchange (CME)* .

Bansal, R., D. Kiku, and M. Ochoa. 2021. Climate Change Risk. *NBER Working Paper* 1:1–57.

Barnett, M. 2023. Climate Change and Uncertainty: An Asset Pricing Perspective. *Management Science* 69:7562–84.

Barnett, M., W. Brock, and L. P. Hansen. 2020. Pricing Uncertainty Induced by Climate Change. *Review of Financial Studies* 33:1024–66.

———. 2021. Climate Change Uncertainty Spillover in the Macroeconomy. *NBER Working Paper* 1:1–66.

Bergman, N. K., R. Iyer, and R. T. Thakor. 2020. The Effect of Cash Injections: Evidence from the 1980s Farm Debt Crisis. *Review of Financial Studies* 33:5092–130.

Bernstein, A., M. T. Gustafson, and R. Lewis. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134:253–72.

Bilal, M., and E. Rossi-Hansberg. 2023. Anticipating Climate Change Across the United States. *Working Paper* 1:1–52.

Black, F. 1976. The pricing of commodity contracts. *Journal of Financial Economics* 3:167–79.

Bollerslev, T., G. Tauchen, and H. Zhou. 2009. Expected Stock Returns and Variance Risk Premia. *Review of Financial Studies* 22:4463—4492.

Bortolan, L., A. Dey, and L. Taschini. 2023. Nailing Down Volatile Temperatures: Examining their Effects on Asset Prices. *Working Paper* 1:1–58.

Brown, J. R., M. T. Gustafson, and I. T. Ivanov. 2021. Weathering Cash Flow Shocks. *Journal of Finance* 76:1731–72.

Busse, M. R., D. G. Pope, J. C. Pope, and J. Silva-Risso. 2015. The Psychological Effect of Weather on Car Purchases. *Quarterly Journal of Economics* 130:371–414.

Campbell, S. D., and F. X. Diebold. 2005. Weather Forecasting for Weather Derivatives. *Journal of the American Statistical Association* 100:6–16.

Cao, M., and J. Wei. 2004. Weather Derivatives Valuation and the Market Price of Weather Risk. *Journal of Futures Markets* 24:1065–89.

Carr, P., and L. Wu. 2009. Variance Risk Premia. *Review of Financial Studies* 22:1311–41.

Chaney, C., D. Sraer, and D. Thesmar. 2012. The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. *American Economic Review* 102:2381—2409.

Chen, S., H. Doshi, and S. Seo. 2023. Synthetic Options and Implied Volatility for the Corporate Bond Market. *Journal of Financial and Quantitative Analysis* 58:1295–325.

Chincarini, D. 2011. Temperature Surprises: an Empirical Analysis of the Weather Derivatives Market. *Journal of Futures Markets* 31:1–33.

Choi, D., Z. Gao, and W. Jiang. 2020. Attention to Global Warming. *Review of Financial Studies* 33:1112–45.

Choi, H. Y., P. Mueller, and A. Vedolin. 2017. Bond Variance Risk Premiums. *Review of Finance* 21:987–1022.

Colacito, R., B. Hoffmann, and T. Pham. 2019. Temperature and growth: A panel analysis of the United States. *Journal of Money Credit and Banking* 51:313–68.

Cummins, J. D., D. Lalonde, and R. D. Phillips. 2004. The basis risk of catastrophic-loss index securities. *Journal of Financial Economics* 71:77–111.

Dell, M., B. F. Jones, and B. A. Olken. 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics* 4:66–95.

———. 2015. What Do We Learn from the Weather? The New Climate–Economy Literature. *Journal of Economic Literature* 52:740–98.

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

Dew-Becker, I., S. Giglio, A. Le, and M. Rodriguez. 2017. The Price of Variance Risk. *Journal of Financial Economics* 123:225–50.

Donadelli, M., M. Juppner, N. Paradiso, and C. Schlag. 2022. Temperature Volatility Risk. *Working Paper* 1:1–55.

Dorfleitner, G., and M. Wimmer. 2010. The pricing of temperature futures at the Chicago Mercantile Exchange. *Journal of Banking and Finance* 34:1360–70.

Drechsler, I. 2013. Uncertainty, Time-Varying Fear, and Asset Prices. *Journal of Finance* 68:1843–89.

Drechsler, I., and A. Yaron. 2011. What's Vol Got to Do with It. *Review of Financial Studies* 24:1–45.

Du, D., R. Elkamhi, and J. Ericsson. 2019. Time-Varying Asset Volatility and the Credit Spread Puzzle. *Journal of Finance* 74:1841–85.

Elkhami, R., C. Jo, and M. Salerno. 2023. Measuring "State-level" Economic Policy Uncertainty. *Journal of Financial and Quantitative Analysis (Forthcoming)* 0:1–90.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel. 2020. Hedging Climate Change News. *Review of Financial Studies* 33:1182–216.

Feunou, B., M. R. Jahan-Parvar, and C. Okou. 2018. Downside variance risk premium. *Journal of Financial Econometrics* 16:341—383.

Froote, K. A. 2001. The market for catastrophe risk: a clinical examination. *Journal of Financial Economics* 60:529–71.

Froote, K. A., and P. G. J. O Connell. 2008. On the pricing of intermediated risks: Theory and application to catastrophe reinsurance. *Journal of Banking and Finance* 32:69–85.

Garmaise, M. J., and T. J. Moskowitz. 2009. Catastrophic Risk and Credit Markets. *Journal of Finance* 66:657–707.

Giglio, S., M. Maggiori, D. Rao, J. Stroebel, and A. Weber. 2023. Climate Change and Long-Run Discount Rates: Evidence from Real Estate. *Review of Financial Studies* 34:3527–71.

Ginglinger, E., and Q. Moreau. 2023. Climate Risk and Capital Structure. *Management Science (Forthcoming)* 0:0–.

Goetzmann, W. N., D. Kim, A. Kumar, and Q. Wang. 2020. Weather-Induced Mood, Institutional Investors, and Stock Returns. *Review of Financial Studies* 28:73–111.

Goldsmith-Pinkham, P., M. Gustafson, R. C. Lewis, and M. Schwert. 2023. Sea Level Rise Exposure and Municipal Bond Yields. *Review of Financial Studies (Forthcoming)* 0:1–53.

Griffin, P. A., D. H. Lont, and M. Lubberink. 2023. The Nonlinear Effects of Extreme Temperature Heat Spells on Financial Performance. *Working Paper* 1:1–56.

Hain, L., J. F. Koebbel, and M. Leippold. 2023. Bounding the Impact of Hazard Interdependence on Climate Risk. *Working Paper* 1:1–49.

Hardle, W. K., and B. Lopez-Cabrera. 2012. The Implied Market Price of Weather Risk. *Applied Mathematical Finance* 19:59–95.

Hardle, W. K., B. Lopez-Cabrera, and H. W. Teng. 2015. State price densities implied from weather derivatives. *Insurance: Mathematics and Economics* 64:106–25.

———. 2016. Localizing Temperature Risk. *Journal of the American Statistical Association* 111:1491–508.

Hess, R. 2024. Pricing and Hedging of Temperature Derivatives in a Model with Memory. *International Journal of Theoretical and Applied Finance (FORTHCOMING)* 0:1–24.

Heston, S. L., and K. Todorov. 2023. Exploring the Variance Risk Premium Across Assets. *Working Paper* 1:1–38.

Huynh, T. D., and Y. Xia. 2021. Climate Change News Risk and Corporate Bond Returns. *Journal of Financial and Quantitative Analysis* 56:1985–2009.

Ilhan, E., P. Krueger, Z. Sautner, and L. Starks. 2023. Climate Risk Disclosure and Institutional Investors. *Review of Financial Studies* 36:2617–50.

Institute, C. D. 2021. Hedging against climate risks using weather derivatives: Alain Brisebois of CWP Energy discusses these often-misunderstood products. *Investment Executive* .

Jones, B. F., and B. A. Olken. 2010. Climate shocks and exports. *American Economic Review* 100:454–9.

Kirk, M., D. Stice, and H. Stice. 2022. The Real Effects of Weather on Firm Performance, Analyst Forecasts, and Stock Prices. *Working Paper* 1:1–64.

Kruttli, M. S., B. Roth Tran, and S. W. Watugala. 2023. Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. *Journal of Finance (Forthcoming)* 0:1–113.

Liu, Y., and J. C. Wu. 2022. Reconstructing the Yield Curve. *Journal of Financial Economics* 142:1395–425.

Lontzek, T., W. Pohl, K. Schmedders, W. Thalhammer, and O. Wilms. 2023. Asset Pricing with Disagreement about Climate Risks. *Working Paper* 1:1–47.

Merton, R. C. 1974. On the pricing of corporate debt: The risk structure of interest rates. *Journal of Financial Economics* 29:449–70.

Miller, W. K., B. Chua, A. Coggins, and M. Mohtadi. 2021. Heat Waves, Climate Change, and Economic Output. *Journal of the European Economic Association* 19:2658–94.

Murfin, J., and M. Spiegel. 2020. Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *Review of Financial Studies* 33:1217–55.

Pankratz, N., R. Bauer, and J. Derwall. 2023. Climate Change, Firm Performance, and Investor Surprises. *Management Science (Forthcoming)* 0:1–47.

Pankratz, N., and C. Schiller. 2023. Climate Change and Adaptation in Global Supply Chain Networks. *Review of Financial Studies (Forthcoming)* 0:1–80.

Perez-Gonzalez, A., and H. Yun. 2013. Risk Management and Firm Value: Evidence from the Weather Derivatives. *Journal of Finance* 68:2143–76.

Pirinsky, C., and Q. Wang. 2006. Does Corporate Headquarters Location Matter for Stock Returns? *Journal of Finance* 61:1991–2015.

Potter, S. 2024. A 25 Billion Market Rises to Blunt Costs of Worsening Weather. *Bloomberg News* .

Purnanandam, A., and D. Weagley. 2016. Can markets discipline government agencies? Evidence from the weather derivatives market. *Journal of Finance* 71:303–34.

Pyun, S. 2019. Variance Risk in Aggregate Stock Returns and Time-Varying Return Predictability. *Journal of Financial Economics* 132:150–74.

Robertson, H. 2023. Use of weather derivatives surges as extreme climate events rock the globe. *Reuters* .

Sautner, Z. 2023. The Climate Change Lab.

Sautner, Z., L. V. Lent, G. Vilkov, and R. Zhang. 2022. Pricing Firm-level Climate Change Exposure. *Management Science (Forthcoming)* 0:1–55.

———. 2023. Firm-level Climate Change Exposure. *Journal of Finance (Forthcoming)* 0:1–110.

Schlenker, W., and C. A. Taylor. 2021. Market Expectations of a Warming Climate. *Journal of Financial Economics* 71:627–40.

Taylor, C. 2021. Replication of Market Expectations of a Warming Climate.

Tomunen, T. 2023. Failure to Share Natural Disaster Risk. *Working Paper Boston College* 1:1–103.

Weagley, D. 2019. Financial Sector Stress and Risk Sharing: Evidence from the Weather Derivatives Market. *Review of Financial Studies* 32:2456–97.

Weitzman, M. L. 2009. On Modelling and Interpreting the Economics of Catastrophic Climate Change. *Review of Economics and Statistics* 91:1–19.

Wu, C. J. 2023. Yield Data.

Zhang, L. 2023. Operating Exposure to Weather, Earnings Predictability, and Analyst Forecast. *Working Paper* 1:1–58.

Zhou, R., J. S. Li, and J. Pai. 2019. Pricing temperature derivatives with a filtered historical simulation approach. *European Journal of Finance* 25:1462–84.

Table 1 Seasonal Strips Futures Options Summary Statistics

	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Atlanta, GA									
Implied Volatility	12,956	0.16	0.16	0.08	3.35	0.08	0.11	0.19	0.21
Open Interest	12,956	968	750	802	1	250	250	1,250	2,250
Time to Maturity (TTM)	12,956	0.26	0.24	0.15	0.35	0.06	0.13	0.37	0.46
Chicago, IL									
Implied Volatility	8,500	0.15	0.12	0.09	1.47	0.06	0.09	0.16	0.3
Open Interest	8,500	958	500	976	2	50	250	1,250	2,250
Time to Maturity (TTM)	8,500	0.23	0.21	0.14	0.35	0.06	0.12	0.34	0.43
Cincinnatti, OH									
Implied Volatility	3,949	0.28	0.29	0.08	−0.2	0.16	0.24	0.33	0.37
Open Interest	3,949	1,149	1,000	733	1	250	750	1,500	2,000
Time to Maturity (TTM)	3,949	0.22	0.22	0.11	0.13	0.07	0.14	0.31	0.37
Dallas, TX									
Implied Volatility	11,608	0.15	0.15	0.06	0.39	0.09	0.11	0.19	0.23
Open Interest	11,608	899	750	694	1	250	300	1,250	2,000
Time to Maturity (TTM)	11,608	0.23	0.23	0.13	0.21	0.06	0.13	0.34	0.42
Las Vegas, NV									
Implied Volatility	4,800	0.1	0.07	0.06	2.66	0.04	0.06	0.11	0.18
Open Interest	4,800	1,490	1,250	1,278	1	250	500	2,500	3,000
Time to Maturity (TTM)	4,800	0.2	0.19	0.13	0.52	0.04	0.1	0.29	0.37
Minneapolis, MN									
Implied Volatility	8,291	0.16	0.13	0.1	1.39	0.07	0.1	0.19	0.33
Open Interest	8,291	849	750	585	1	250	250	1,250	1,500
Time to Maturity (TTM)	8,291	0.23	0.22	0.14	0.23	0.05	0.12	0.34	0.43
New York, NY									
Implied Volatility	20,596	0.15	0.14	0.06	0.59	0.08	0.11	0.19	0.23
Open Interest	20,596	1,095	750	937	2	250	250	1,500	2,500
Time to Maturity (TTM)	20,596	0.26	0.26	0.15	0.25	0.07	0.14	0.38	0.47
Sacramento, CA									
Implied Volatility	2,499	0.16	0.16	0.05	0.13	0.09	0.12	0.19	0.22
Open Interest	2,499	1,380	1,000	962	1	250	500	2,000	2,250
Time to Maturity (TTM)	2,499	0.23	0.21	0.14	0.37	0.06	0.12	0.34	0.44

Note: This table reports the sample statistics of the implied volatility, 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
Cincinnatti, 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 2.1.

Table 3 Municipal Bond Credit Spreads and WVRP (Contemporaneous)

	Panel A: Full Sample			Panel B: $TTM < 15$			Panel C: $TTM > 15$		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t}$	$-1e-3$			$1.2e-3$			$-1.6e-3$		
	(-2.09)			(2.27)			(-1.65)		
$\text{WRVOL}_{c,t}$		-0.01			-0.01			-0.01	
		(-29.03)			(-34.79)			(-11.15)	
$\text{WVRP}_{c,t}$			0.01			0.01			$4.1e-3$
			(20.17)			(26.65)			(7.37)
$XDD_{c,t}$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-3.08)	(2.02)	(0.62)	(-8.79)	(-1.28)	(-3.60)	(1.54)	(2.86)	(2.63)
$TTM_{b,t}$	$-3.1e-3$	$-3.7e-3$	$-3.6e-3$	$-2.8e-3$	$-3.6e-3$	$-3.7e-3$	$-3.1e-3$	$-3.5e-3$	$-3.4e-3$
	(-12.98)	(-15.65)	(-15.43)	(-11.68)	(-15.18)	(-15.22)	(-7.28)	(-8.16)	(-7.94)
$\log(\text{AmtOut/DollVolume})_{b,t}$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-13.86)	(-13.96)	(-13.88)	(-18.81)	(-18.99)	(-18.81)	(-2.31)	(-2.37)	(-2.32)
R^2	81.17	81.47	81.32	84.77	85.36	85.12	80.73	80.84	80.78
N obs	62,748	62,748	62,748	37,056	37,056	37,056	25,692	25,692	25,692
Bond CUSIP Fixed Effects	Y	Y	Y	Y	Y	Y	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 bond credit spreads (at time t) regressed on t. $\text{WRVOL}_{c,t}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly $\text{WIVOL}_{c,t}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time t and $\text{WVRP}_{c,t}$ is 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. Municipal bond 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 municipal bond individual CUSIP identifier as well as year quarter fixed effects. Panel A reports the results for the full sample of municipal bonds and Panels B and C report the panel regression results for the subsets of municipal bonds with time to maturity less and greater than 15 years respectively. t-statistics are presented in parentheses under the coefficients.

Table 4 Corporate Credit Spreads and WVRP (Contemporaneous)

	Panel A: Full Sample			Panel B: $TTM < 15$			Panel C: $TTM > 15$		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t}$	-0.01			-0.01			$-3e-3$		
	(-4.16)			(-3.99)			(-1.86)		
$\text{WRVOL}_{c,t}$		-0.01			-0.02			$-4.3e-3$	
		(-7.30)			(-7.70)			(-3.07)	
$\text{WVRP}_{c,t}$			0.01			0.01			$1.5e-3$
			(5.43)			(3.90)			(1.27)
$XDD_{c,t}$	0.00	0.00	0.00	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-2.04)	(-1.94)	(-0.68)	(-2.11)	(-2.09)	(-0.93)	(1.67)	(1.89)	(2.33)
$TTM_{b,t}$	$0.1e-3$	$0.7e-3$	$-0.2e-3$	$0.8e-3$	$1.4e-3$	$0.4e-3$	$-1.9e-3$	$-1.8e-3$	$-2.1e-3$
	(0.16)	(0.93)	(-0.28)	(0.55)	(0.94)	(0.25)	(-1.91)	(-1.74)	(-2.04)
$Rating_{b,t}$	0.01	0.01	0.01	0.01	0.01	0.01	$1.9e-3$	$1.9e-3$	$1.9e-3$
	(9.37)	(9.39)	(9.38)	(59.95)	(60.12)	(59.97)	(17.43)	(17.45)	(17.39)
$\log(\text{AmtOut/DollVolume})_{b,t}$	0.00	$-0.1e-3$	0.00	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-0.23)	(-0.34)	(-0.26)	(-2.02)	(-2.2)	(-2.06)	(-0.94)	(-1.03)	(-0.92)
R^2	67.26	67.29	67.27	67.83	67.86	67.83	70.51	70.53	70.51
N obs	56,949	56,949	56,949	45,089	45,089	45,089	11,860	11,860	11,860
Bond CUSIP Fixed Effects	Y	Y	Y	Y	Y	Y	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 corporate bond credit spreads (at time t) regressed on t. $\text{WRVOL}_{c,t}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly $\text{WIVOL}_{c,t}$ is the weather seasonal strip options monthly average option implied volatility for county c at time t and $\text{WVRP}_{c,t}$ is 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. Corporate bond controls include the remaining time to maturity (TTM, in years) and the credit rating of bond i at time t. 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 5 Stock VRP and the WVRP (Contemporaneous)

	Panel A: Full Sample			Panel B: Full Sample + EPU			Panel C: Full Sample + EJS SEPU		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t}$	0.01			0.01			0.01		
	(0.23)			(0.34)			(0.24)		
$\text{WRVOL}_{c,t}$		-0.01			-0.01			-0.01	
		(-0.61)			(-0.57)			(-0.61)	
$\text{WVRP}_{c,t}$			0.03			0.03			0.03
			(2.16)			(2.23)			(2.15)
$XDD_{c,t}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.34)	(-1.36)	(-0.24)	(-0.71)	(-1.97)	(-0.81)	(-0.32)	(-1.37)	(-0.22)
EPU_t				0.01	0.01	0.01			
				(2.77)	(3.18)	(2.77)			
EJS $\text{SEPU}_{c,t}$							$-0.8e-3$	$-0.4e-3$	$-0.9e-3$
							(-0.27)	(-0.14)	(-0.30)
R^2	78.76	74.87	78.94	78.77	78.76	74.87	78.76	74.88	78.94
N obs	21,881	25,350	21,722	21,881	25,350	21,722	21,881	25,350	21,722
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year x Quarter Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	Y

Note: Note: This table reports monthly panel regressions with the dependent variable being the firm level stock variance risk premia (at time t) regressed on t. $\text{WRVOL}_{c,t}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly $\text{WIVOL}_{c,t}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time t and $\text{WVRP}_{c,t}$ is the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$. $XDD_{c,t}$ is the forecasted value of the end of the month seasonal strip futures contract payoff for county c at time t. All regression estimates include firm fixed effects and year quarter fixed effects. t-statistics are in parentheses under the coefficients with standard errors clustered by firm.

Table 6 Municipal Bond Credit Spreads and WVRP (Predictive)

	Panel A: Full Sample			Panel B: $TTM < 15$			Panel C: $TTM > 15$		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t-1}$	$-4e-3$			-0.01			-0.01		
	(6.94)			(-9.63)			(-5.44)		
$\text{WRVOL}_{c,t-1}$		0.01			0.01			0.01	
		(12.39)			(11.85)			(6.86)	
$\text{WVRP}_{c,t-1}$			-0.01			-0.01			-0.01
			(-18.13)			(-15.62)			(-9.31)
$XDD_{c,t-1}$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(10.64)	(8.66)	(4.98)	(6.06)	(6.01)	(3.35)	(4.13)	(5.51)	(3.60)
$TTM_{b,t-1}$	$-3.3e-3$	$0.2e-3$	$0.2e-3$	$0.3e-3$	$0.3e-3$	$0.3e-3$	$0e-3$	$0e-3$	$0.1e-3$
	(-12.69)	(2.68)	(3.90)	(4.91)	(4.43)	(5.44)	(0.18)	(0.01)	(0.65)
$\log(\text{AmtOut}/\text{DollVolume})_{b,t-1}$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$	$0e-3$	$0e-3$	$0e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-3.93)	(-4.55)	(-4.31)	(-2.88)	(-3.03)	(-2.93)	(-2.91)	(-2.91)	(-2.75)
R^2	80.82	80.77	80.84	84.71	84.74	84.79	79.84	79.86	79.90
N obs	58,769	58,769	58,769	34,837	34,837	34,837	23,932	23,932	23,932
Bond CUSIP Fixed Effects	Y	Y	Y	Y	Y	Y	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 bond credit spreads (at time t) regressed on $t-1$. $\text{WRVOL}_{c,t-1}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time $t-1$. Similarly $\text{WIVOL}_{c,t-1}$ is the weather seasonal strip options monthly average option implied volatility for county c at time $t-1$ and $\text{WVRP}_{c,t-1}$ 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 $t-1$. Municipal bond controls include the remaining time to maturity (TTM, in years) and the $\log(\text{AmtOut}/\text{DollVolume})_{i,t-1}$ which is the log-ratio of the bond outstanding over the amount of dollar traded volume of the bond i at time $t-1$. All regression estimates include fixed effects for the municipal bond individual CUSIP identifier as well as year quarter fixed effects. Panel A reports the results for the full sample of municipal bonds and Panels B and C report the panel regression results for the subsets of municipal bonds with time to maturity less and greater than 15 years respectively. t-statistics are presented in parentheses under the coefficients.

Table 7 Corporate Credit Spreads and WVRP (Predictive)

	Panel A: Full Sample			Panel B: $TTM < 15$			Panel C: $TTM > 15$		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t-1}$	-0.01			-0.01			-0.01		
	(-6.61)			(-6.47)			(-2.73)		
$\text{WRVOL}_{c,t-1}$		$-0.2e-3$			$-1e-3$			$2.1e-3$	
		(-0.16)			(-0.52)			(1.37)	
$\text{WVRP}_{c,t-1}$			-0.01			-0.01			-0.01
			(-7.29)			(-6.98)			(-3.99)
$XDD_{c,t-1}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-4.12)	(-2.03)	(-2.18)	(-4.25)	(-2.32)	(-2.33)	(0.35)	(1.82)	(1.24)
$TTM_{b,t-1}$	$0.7e-3$	$0.6e-3$	$0.7e-3$	$1e-3$	$0.9e-3$	$1.1e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(1.61)	(1.37)	(1.66)	(1.63)	(1.38)	(1.68)	(-0.83)	(-0.96)	(-0.81)
$Rating_{b,t-1}$	0.01	0.01	0.01	0.01	0.01	0.01	$1.5e-3$	$1.5e-3$	$1.5e-3$
	(8.59)	(8.58)	(8.58)	(8.32)	(8.30)	(8.30)	(3.46)	(3.45)	(3.45)
$\log(\text{AmtOut/DollVolume})_{b,t-1}$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.6e-3$	$-0.6e-3$	$-0.6e-3$	0.00	0.00	0.00
	(-1.62)	(-1.61)	(-1.59)	(-2.56)	(-2.55)	(-2.54)	(-0.25)	(-0.21)	(-0.21)
R^2	67.52	67.50	67.51	68.66	68.63	68.65	70.53	70.51	70.55
N obs	56,013	56,013	56,013	44,284	44,284	44,284	11,729	11,729	11,729
Bond CUSIP Fixed Effects	Y	Y	Y	Y	Y	Y	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 corporate bond credit spreads (at time t) regressed on $t-1$. $\text{WRVOL}_{c,t-1}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time $t-1$. Similarly $\text{WIVOL}_{c,t-1}$ is the weather seasonal strip options monthly average option implied volatility for county c at time $t-1$ and $\text{WVRP}_{c,t-1}$ 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 municipal bonds and Panels B and C report the panel regression results for the subsets of municipal 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 Stock VRP and the WVRP (Predictive)

	Panel A: Full Sample			Panel B: Full Sample + EPU			Panel C: Full Sample + EJS SEPU		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t-1}$	-0.02			-0.01			-0.01		
	(-1.16)			(-1.00)			(-1.13)		
$\text{WRVOL}_{c,t-1}$		0.04			0.04			0.04	
		(4.08)			(4.07)			(4.05)	
$\text{WVRP}_{c,t-1}$			-0.05			-0.05			-0.05
			(-5.07)			(-4.89)			(-4.91)
$XDD_{c,t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-1.62)	(-0.57)	(-1.82)	(-2.13)	(-1.51)	(-2.46)	(-1.39)	(-0.46)	(-1.62)
$\text{StockVRP}_{s,t-1}$	0.67	0.68	0.67	0.67	0.68	0.67	0.67	0.68	0.67
	(26.50)	(28.62)	(26.60)	(26.45)	(28.57)	(26.55)	(26.49)	(28.62)	(26.59)
EPU_{t-1}				0.01	0.01	0.01			
				(3.18)	(4.43)	(2.85)			
$\text{EJS SEPU}_{c,t-1}$							-0.01	$-3.7e-3$	-0.01
							(-2.89)	(-1.92)	(-2.63)
R^2	87.44	85.01	87.52	87.45	85.02	87.53	87.45	85.01	87.53
N obs	$21,586$	$25,030$	$21,429$	$21,586$	$25,030$	$21,429$	$21,586$	$25,030$	$21,429$
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	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 firm level stock variance risk premia (at time $t+1$) regressed on t. $\text{WRVOL}_{c,t}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly $\text{WIVOL}_{c,t}$ is the weather seasonal strip options monthly average option implied volatility for county c at time t and $\text{WVRP}_{c,t}$ is the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$. $XDD_{c,t-1}$ is the forecasted value of the end of the month seasonal strip futures contract payoff for county c at time $t-1$. All regression estimates include firm fixed effects and year quarter fixed effects. t-statistics are in parentheses under the coefficients with standard errors clustered by firm.

Table 9 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 10 Robustness: Stock VRP and the WVRP (Predictive)

	Panel A: Full Sample			Panel B: Full Sample + EPU			Panel C: Full Sample + EJS SEPU		
Variable	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\text{WIVOL}_{c,t-1}$	-0.01			-0.01			-0.01		
	(-1.59)			(-1.60)			(-1.60)		
$\text{WRVOL}_{c,t-1}$		0.05			0.05			0.05	
		(2.83)			(2.83)			(2.83)	
$\text{WVRP}_{c,t-1}$			-0.02			-0.02			-0.02
			(-2.93)			(-2.90)			(-2.89)
$XDD_{c,t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-1.61)	(-1.01)	(-0.05)	(-1.62)	(-1.01)	(-0.04)	(-1.62)	(-1.01)	(-0.05)
$\text{StockVRP}_{s,t-1}$	0.60	0.67	0.50	0.60	0.67	0.50	0.60	0.67	0.50
	(11.08)	(20.57)	(12.51)	(11.08)	(20.57)	(12.52)	(11.08)	(20.55)	(12.50)
EPU_{t-1}	$3.8e-3$	0.01	$2.4e-3$	$3.8e-3$	0.01	$2.4e-3$	$3.8e-3$	0.01	$2.4e-3$
	(1.94)	(2.24)	(0.80)	(1.96)	(2.24)	(0.80)	(1.96)	(2.23)	(0.81)
cc risk $\text{ew}_{s,t-1}$	5.49	1.64	2.17						
	(1.75)	(0.52)	(0.70)						
cc expo $\text{ew}_{s,t-1}$				-0.48	1.64	-1.00			
				(-0.87)	(0.52)	(-0.94)			
op risk $\text{ew}_{s,t-1}$							-5.35	-29.22	-34.85
							(-0.65)	(-2.70)	(-2.50)
R^2	91.81	92.16	96.36	91.81	92.16	96.36	91.81	92.16	96.36
N obs	21,156	15,189	9,976	21,156	15,189	9,976	21,156	15,189	9,976
Firm Fixed Effects	Y	Y	Y	Y	Y	Y	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 firm level stock variance risk premia (at time $t+1$) regressed on t. $\text{WRVOL}_{c,t}$ is the weather futures realized volatility of the seasonal strip futures contracts for county c at time t. Similarly $\text{WIVOL}_{c,t}$ is the weather seasonal strip options monthly average option implied volatility for county c at time t and $\text{WVRP}_{c,t}$ is the difference between the $\text{WIVOL}_{c,t}$ and $\text{WRVOL}_{c,t}$ for county c at time t. $XDD_{c,t-1}$ is the forecasted value of the end of the month seasonal strip futures contract payoff for county c at time $t-1$. All regression estimates include firm fixed effects and year quarter fixed effects. t-statistics are in parentheses under the coefficients with standard errors clustered by firm.

Table 11 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.

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 Futures Returns Summary Statistics

Panel A: Daily Raw Futures Returns (monthly non seasonal futures only)									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
All	39,405	$-0.4e-3$	0.00	0.06	0.55	−0.04	−0.01	0.01	0.03
CA	4,451	$-1.4e-3$	0.00	0.06	−0.91	−0.04	−0.01	0.01	0.04
GA	5,123	$0e-3$	0.00	0.05	0.9	−0.04	−0.01	0.01	0.04
IL	5,077	$-0.4e-3$	0.00	0.06	−0.07	−0.04	−0.01	0.01	0.04
MN	4,478	$0.8e-3$	0.00	0.07	1.7	−0.04	−0.01	0.01	0.03
NV	4,854	$-1.3e-3$	0.00	0.06	0.56	−0.03	−0.01	0.01	0.03
NY	5,162	$-0.2e-3$	0.00	0.06	0.38	−0.03	−0.01	0.01	0.03
OH	5,119	$-0.1e-3$	0.00	0.05	0.39	−0.04	−0.01	0.01	0.04
TX	5,141	$-0.7e-3$	0.00	0.06	0.62	−0.04	−0.01	0.01	0.04
Panel B: Monthly Futures Return Volatility (monthly non seasonal futures only)									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
All	1,637	0.59	0.42	0.48	1.49	0.18	0.27	0.74	1.33
CA	185	0.6	0.45	0.45	1.34	0.19	0.32	0.76	1.31
GA	213	0.56	0.44	0.39	1.53	0.19	0.3	0.72	1.04
IL	211	0.63	0.39	0.54	1.32	0.2	0.26	0.83	1.62
MN	186	0.67	0.36	0.6	1.16	0.18	0.24	0.94	1.93
NV	200	0.53	0.36	0.44	1.37	0.13	0.22	0.7	1.15
NY	215	0.54	0.37	0.47	1.93	0.18	0.27	0.58	1.28
OH	213	0.6	0.45	0.46	1.57	0.2	0.29	0.71	1.29
TX	214	0.58	0.46	0.45	1.48	0.19	0.27	0.72	1.27

Note: Panel A reports average daily raw futures returns (monthly futures) 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. Panel B monthly return volatility from daily futures returns per city/state. In this table reports the city/state (airports) used in our analysis are: 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.3 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.4 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.5 : 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 all control and weather derivatives measures from Table A.4. The sample period is monthly observations from January 2006 to December 2019.