Weather Variance Risk Premia*

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

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Abstract

We analyze the information content of a variance risk premia extracted from the weather derivatives contracts written on the local temperature of individual U.S. cities. We term this the Weather Variance Risk Premia (WVRP). By constructing the WVRP measure from the CME's weather futures and options contracts, we examine the role of weather variance risk on bond credit spreads of local corporations and municipalities. Our results indicate informativeness of weather derivatives market as a local risk factor priced in the bond returns of local corporations and municipalities. Our result is robust to controlling state level economic uncertainty measures.

JEL Classification: Q02, G13

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

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

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

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

¶Hankamer School of Business, Baylor University, virgilio_zurita@baylor.edu

1 Introduction

Considerable amount of research have identified that information embedded in the options contracts provide significantly richer understanding of various financial markets. For example, the VIX index constructed from index options is now widely used everywhere by both academics and practitioners. One of the main essence the options contract can help infer is the aggregate investors' risk preference. In particular, risk preferences on higher moments of stock returns are unobtainable without the aid of derivatives contracts.

While the most of focus have been placed in the equity markets so far, in this paper we propose and construct weather uncertainty measures from exchange traded weather Futures contracts and options contracts written on them. Underlying of these contracts are temperature indices of different cities across the U.S. and Europe. Our particular interest is the cost of hedging local temperature fluctuations using the weather options and the benefits of the hedging on local assets such as local firm's stock return volatility and credit spreads (both corporate and municipal). 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 estimate realized volatility (i.e. investors are paying more to hedge stock return volatility risk than risk they are exposed to) and Bollerslev, Tauchen, and Zhou (2009) who find that the market variance risk premia positively predicts U.S. stock index returns. In a similar way, we construct a weather variance risk premia, defined as the difference between weather Futures option implied volatility and the weather Futures volatility, and assess it's impact on the local firms in and around cities where weather derivatives are traded.

To empiricaly study this, we raise questions concerning the relationship between the weather variance risk premia and its impact on local firms and municipalities. Greater weather variance risk premia indicates investors' risk aversion against local temperature fluctuations. In other words, investors fear that firms and municipalities operating in local area being exposed to natural disaster risk in the future that could severely hurt their future operations. We investigate whether this is true by looking at three main measures: local municipal bond credit spreads, local corporate bond credit spreads, and local corporation's stock return variance risk premia. Bollerslev, Tauchen, and Zhou (2009) and Chen, Doshi, and Seo (2023) find that variance risk premia of stock and bond markets are positively related to the expected returns, respectively. Extrapolating their results, we expect the weather variance risk premia to also play a similar role to the local assets, thus positively predicting the expected bond returns of municipalities and local firms. To test this, we run predictive regressions to see whether weather derivatives risk premia negatively predicts the bond credit spreads, thus positive expected return.

We find that our weather variance risk premia is negatively priced in the local cross section of stock return variance risk premia, corporate and municipal bond credit spreads. Our results imply a higher cost of hedging temperature volatility leads to a lower cost of hedging equity volatility uncertainty as well as lower corporate credit spreads, and localized municipal credit spreads. Our weather variance risk premia have larger negative coefficients on the impact of municipal bond credit spreads with longer term to maturity than shorter term to maturity indicating the effectiveness of weather futures in hedging decreases credit spreads more for longer term than shorter term bonds. Correspondingly weather variance risk premia has a larger negative coefficients on the impact of corporate credit spreads with shorter term to maturity than longer term to maturity indicating the effectiveness of weather futures in hedging decreases corporate credit spreads more for shorter term than longer term bonds. Our results imply the benefits of hedging temperature volatility on the local financial economy.

A large literature has been developed and continues to be developed that studies how to measure economic uncertainty and it's impact on the real and financial economy.[1] Recently Baker, Bloom, and Terry (2023) use various measures of disasters to estimate the impact of uncertainty shock impacts on the macro economy. The impact of the local uncertainty shocks has been shown to have a forward looking impact on local stock and corporate bond

[1] 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.

returns (see Bali, Brown, and Tang (2017) and Bali, Subrahmanyam, and Wen (2021)).

Our paper contributes to three strands of literature: (1) literature on climate and temperature uncertainty, (2) the literature on weather derivatives and (3) variance risk premia.

First our paper contributes to the literature on climate and temperature uncertainty, see for instance: 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 (2023) as well as many others. Several papers have documented the impact of temperature shocks on macroeconomic output and growth.[2] Acharya et al. (2022) study the premium in the cross section of US stocks and spread component in corporate and municipal bonds for the physical climate risk across all regions in the US. Bansal, Kiku, and Ochoa (2021), Barnett (2023) and Donadelli et al. (2022) study the size of the premia required in the cross section of US stocks for temperature changes over the last decades.[3] Our results imply the benefits of the hedging temperature volatility on the local financial economy.

Secondly we contribute to the literature on weather derivatives, the class of securities whose payoff is contingent on the specific temperature at a particular city.[4] Several papers in this literature have looked at the impact of the inception of an exchange to trade weather derivatives market on: (i) firm risk management practices in the utilities industry (see Perez-Gonzalez and Yun (2013)), (ii) the impact on the improvement of weather

[2]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).

[3]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.

[4]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.

forecasting of 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 the weather derivatives literature is the work of Weagley (2019), who finds that the limited financial intermediary risk bearing capacity increases the 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 how to price weather derivatives beginning with (i) Cao and Wei (2004) and Zhou, Li, and Pai (2019) who price weather derivatives in general equilibrium (ii) Campbell and Diebold (2005), Dorfleitner and Wimmer (2010) Chincarini (2011) who focus on pricing weather futures (iii) Hardle and Lopez-Cabrera (2012) and Hardle, Lopez-Cabrera, and Teng (2015) who focus on applications of the weather options and futures to 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 that we show the usefulness of the weather derivatives in hedging a large cross section of local temperature variations on the corresponding local underlying firm stock, corporate bonds, and municipal bonds. Our results imply the benefits of the hedging temperature volatility on the local financial economy.

The third literature that our paper contributes to is the growing literature of the variance risk premia. Since the seminal findings of Carr and Wu (2009) which find that in the cross section of U.S. stocks, the cost of hedging stock volatility risk inferred from equity options is higher than the estimate realized volatility (i.e. investors are paying more to hedge stock volatility risk than risk they are exposed to) and Bollerslev, Tauchen, and Zhou (2009) who show that the variance risk premia positively predicts U.S. stock index returns, a fleury of research has gone into studying different forms of hedging and understanding variance risk across different asset classes.[5] To this literature our paper contributes a novel variance risk

[5]Additionally different measures of variance risk premia have been developed in different asset classes as investors use derivatives different underlying assets to hedge future asset risk. For example variance risk premiums derived using derivatives from interest rate futures bond risk premia developed from U.S. treasury interest rate futures (see Choi, Mueller, and Vedolin (2017)) also corporate bond variance risk premia has

premia measure (called weather variance risk premia $WVRP$) that is derived from options on heating and cooling index seasonal strip weather futures.

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).[6] Investor or managerial 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), 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.

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 with several avenues of future research.

2 Data and Methodology

2.1 Weather Derivatives Data

The Chicago Mercentile Exchange (CME) introduced standardized *monthly* weather derivative contracts in 1999. In general the monthly weather derivative contract's payoff is based on the average daily temperature taken at the airport weather station at a specific city. For contracts traded on the CME, the specific payoff of the standard monthly temperature contracts are based on either a heating degree day (HDD) index or a cooling degree day

been developed using options on credit default swap indices (see Chen, Doshi, and Seo (2023)) as well as see Heston and Todorov (2023) for commodities markets. Additionally see Bakshi and Kapadia (2003), Dew-Becker et al. (2017) and Feunou, Jahan-Parvar, and Okou (2018).

[6] Fleming, Kirby, and Ostdiek (2006) find higher comovement of returns and volatilities of commodities during weather sensitive trading periods.

(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 listed and traded during the months of the traditional cooling season which runs from May through September.

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

where D_t is the number of days in month t, $T_{i,d}$ 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 the *monthly* HDD (CDD) indices for a specific city i during month t. The contract price quotes are in unites of \$20 hence the payoffs of the HDD (CDD) indices are $20 \times \mathrm{HDD}_{i,t}$ ($20 \times \mathrm{CDD}_{i,t}$).

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 able to trade a bundled package of months during the heating or cooling season.

All option contracts on weather futures (monthly and seasonal strip) 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) and Purnanandam and Weagley (2016). Purnanandam and Weagley (2016) and Weagley (2019), however, these papers have used U.S. monthly temperature futures and options and not the seasonal strips. 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 local temperature futures in order to hedge their risk exposure to small changes in 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 cities New York Laguardia/New York (LGA), Chicago/Illinois O'Hare (ORD), Dallas-Fort Worth/Texas (DFW), Minneapolis-Saint Paul/Minnesota (MSP). See Table 1 for more information regarding the specific code used from the CME. The seasonal strip options and futures data set spans from January 2006 to December 2022.

INSERT TABLE 1 HERE

We apply several filters to our seasonal strip futures and seasonal strip options data set before beginning our analysis. We remove option implied volatilities that are (i) missing (ii) zero or (iii) greater than 100%. Additionally we remove futures and options quotes in which open interest is either zero or missing. Table 2 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 mentioned. Average seasonal strip option implied volatility ranges from 0.27 to 0.59 and ranges from 0.1 (10th percentile) to 0.91 (90th percentile). 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 1153 units with range 50 units (10th percentile) to 2500 units (90th percentile).

INSERT TABLE 2 HERE

Our second set of weather derivatives data is the monthly weather futures of the 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). We obtain daily prices of monthly weather futures contracts are obtained from Schlenker and Taylor (2021).[7] The monthly futures data set spans from January 2006 to December 2019. Table

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

3 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. Across all cities the average daily return is negative and close to zero (median is zero) ranging from -0.04 (10th percentile) to 0.04 (90th percentile) being mostly symmetric across cities.

Table 3 Panel B monthly return volatility from daily futures returns per city/state (volatility estimates are annualized). The annualized realized volatility of monthly futures ($\text{WRVOL}_{c,t}$ for city/state c at time t) average 0.53 to 0.67 ranging from 0.13 (10th percentile) to 1.93 (90th percentile) exhibiting substantial heterogeneity and large positive skewness across cities.

INSERT TABLE 3 HERE

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

where $F_{HDD,s,d}$ ($F_{CDD,s,d}$) is the weather monthly futures HDD (CDD) contract price on day d for city s which are only available during the months of Nov.,...Apr. (May.,...Oct.) respectively. Where $\sqrt{\widehat{\mathbb{VAR}}(\cdot)}$ is the sample volatility of the daily weather monthly futures HDD (CDD) contract price $F_{HDD,s,d}$ ($F_{CDD,s,d}$) returns computed for each county c, across all days d of the calendar month t. The weather seasonal strip futures realized volatility ($\text{WRVOLss}_{c,t}$) county c at time t is constructed analogously to the weather monthly futures realized volatility except using the weather seasonal strips data.

The weather seasonal strip options average option implied volatility ($\text{WIVOLss}_{c,t}$) across all weather seasonal strip options for city c at time t for each month. We define the weather seasonal strip variance risk premia ($\text{WVRPss}_{c,t}$) for each month t for each city c as the difference between the $\text{WIVOLss}_{c,t}$ and $\text{WRVOLss}_{c,t}$.

$$\text{WVRPss}_{s,t} = \begin{cases} \text{WIVOLss}_{HDD,s,t} - \text{WRVOLss}_{HDD,s,t} & \text{if } t = \text{Nov.,...Apr.} \\ \text{WIVOLss}_{CDD,s,t} - \text{WRVOLss}_{CDD,s,t} & \text{if } t = \text{May.,...Oct.} \end{cases} \tag{2.3}$$

where

$$\begin{aligned} \text{WRVOLss}_{HDD,s,t} &= \sqrt{\widehat{\mathbb{VAR}}\left(\frac{Fss_{HDD,s,d} - Fss_{HDD,s,d-1}}{Fss_{HDD,s,d-1}}\right)} \\ \text{WRVOLss}_{CDD,s,t} &= \sqrt{\widehat{\mathbb{VAR}}\left(\frac{Fss_{CDD,s,d} - Fss_{CDD,s,d-1}}{Fss_{CDD,s,d-1}}\right)} \end{aligned} \tag{2.4}$$

where $\text{WRVOLss}_{HDD,s,t}$ ($\text{WRVOLss}_{CDD,s,t}$) are the components of the weather seasonal strips realized volatility during the months of Nov.,...Apr. (May.,...Oct.) respectively. The $Fss_{HDD,s,d}$ ($Fss_{CDD,s,d}$) is the weather seasonal strip futures HDD (CDD) contract price on day d for city s only available during the months of Nov.,...Apr. (May.,...Oct.) respectively.

2.1.1 Municipal Bond, Corporate bond, and Equity Data

In order to test our weather variance risk premia's hedging impact for each city on it's 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 located in surrounding city airport for each weather derivatives city location (iii) firm variance risk premia of the firms located in surrounding city airport for each weather derivatives city location.

We obtain 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.[8] Municipal bond level transaction data for each bond CUSIP is obtained MRSB via WRDS. MRSB contains all of the municipal

[8] 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).

bond transactions (date of transaction, price, yield, dollar volume traded) from Jan 3, 2005, to June 30, 2022. We limit our sample to all municipal bonds that were issued from Jan 3, 2005, to June 30, 2022 for our counties of interest described above. We apply several filters to our municipal data set before beginning our analysis. We remove municipal bond trades that have (i) missing or less than one year to maturity (ii) yields that are less than zero or great than 6.65 (iii) missing or zero notional outstanding and (iv) whose trade price is less than 52 or greater than 138 (in order to minimize the impact of outliers).

INSERT TABLE 4 HERE

Table 4 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. Municipal bond remaining time to maturity (TTM, in years). The average individual corporate bond credit spreads is 0.02 (%2) and ranges from $1.1e-3$ at the 10th percentile to 0.04 at the 90th percentile with an average time to maturity of 9.29 years with duration of 6.17 years.

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.[9] 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.

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, financials, asset backed,

[9] 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.

defaulted, and other filters. 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 gap, have a time to maturity that is longer than one year yet shorter than 30 years, and whose bond price is more than 5 and less than 1000.

INSERT TABLE 5 HERE

Table 5 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 surounding weather derivatives. The average individual firm stock variance risk premia is 0.01 (%1) and ranges from -0.11 at the 10th percentile to 0.12 at the 90th percentile. The average individual corporate bond credit spreads is 0.02 (%2) and ranges from $1.1e-3$ at the 10th percentile to 0.04 at the 90th percentile with an average time to maturity of 9.29 years with duration of 6.17 years.

Across all cities, the monthly weather futures realized volatility (WRVOL) is 0.59 and ranges from 0.19 (10th percentile) to 1.33 (90th percentile). Correspondingly the seasonal strips weather futures realized volatility (WRVOLss) is 0.1 and ranges from 0.04 (10th percentile) to 0.19 (90th percentile). The weather seasonal strip options monthly average option implied volatility (WIVOLss) averages 0.44 and ranges from 0.18 (10th percentile) to 0.74 (90th percentile). The resulting monthly weather seasonal strip options variance risk premia WVRPss is 0.29 on average with standard deviation of 0.22 ranges from 0.04 (10th percentile) to 0.61 (90th percentile).

INSERT TABLE 6 HERE

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.[10] Since the estimated yield curve

[10]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).

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 represents less than five percent of our sample.

Climate projections are used 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 on the 5th 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) 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.

We obtain daily prices of monthly weather futures contracts are obtained from Schlenker and Taylor (2021).[11] Using the climate projections we compute the $XDD_{c,t-1}/XDDss_{c,t-1}$ the forecasted value of the end of month (seasonal strip) futures contract payoff for county c at time $t-1$.

We control for state level economic uncertainty using the measure of Baker et al. (2022).[12] As an additional robustness test, we control for state level economic uncertainty using the measure of Elkhami, Jo, and Salerno (2023b).[13]

2.2 Methodology

We test our weather variance risk premia's hedging impact on municipal bond credit spreads, and the local firm variance risk premia aswell as the corporate credit spreads of the local firms

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

[12]We thank the authors for making their state level economic uncertainty measure freely available on their website Bloom (2023).

[13]We thank the authors for making their state level economic uncertainty measure freely available on their website Elkhami, Jo, and Salerno (2023a).

in and around citites with traded weather derivatives. Additionally we test the impact of all our weather volatility uncertainty measures ($\mathrm{WVOL}_{s,t}$) outlined in Section 2.1: $\mathrm{WVOL}_{s,t} = \{\mathrm{WRVOL}_{s,t}, \mathrm{WIVOL}_{s,t}, \mathrm{WRVOLss}_{s,t}, \mathrm{WVRP}_{s,t}\}$.

In order to measure the predictive impact of the weather volatility uncertainty measures on municipal bond credit spreads (as per hypothesis 1) we build on the panel regression specification similar to Acharya et al. (2022) written in equation 2.5.

$$\text{Muni. Spread}_{b,c,t} = \gamma_c + \gamma_t + b_v \cdot \mathrm{WVOL}_{c,t-1} + \phi \cdot X_{b,c,t-1} + \epsilon_{b,c,t} \tag{2.5}$$

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 Z and X include the bond's time to maturity, and log-bond turnover. We also include bond and time (year quarter) fixed effects. Additionally we control for the forecasted value of the end of month (seasonal strip) futures contract payoff for county c at time $t-1$ ($XDD_{c,t-1}/XDDss_{c,t-1}$).

We measure the predictive impact of the weather volatility uncertainty measures on corporate bond credit spreads (as per hypothesis 2) building on the panel regression specification from Acharya et al. (2022) written in equation 2.6.

$$\text{Corp. Spread}_{b,t} = \gamma_s + \gamma_t + b_v \cdot \mathrm{WVOL}_{c,t-1} + \phi \cdot X_{b,s,t-1} + \epsilon_{b,s,t} \tag{2.6}$$

Corp. $\text{Spread}_{b,t}$ is the credit spread during month t of bond b. Control variables in Z and X include the bond's time to maturity, bond credit rating, and log-bond turnover.[14] We also include individual corporate bond and time (year quarter) fixed effects. Additionally we control for the forecasted value of the end of month (seasonal strip) futures contract payoff for county c at time $t-1$ ($XDD_{c,t-1}/XDDss_{c,t-1}$).

[14]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.

We measure the predictive impact of our weather volatility uncertainty measures on firm stock hedging costs, as measured by the individual firm stock variance risk premia, (as per hypothesis 3) we build on the panel regression specification from Kruttli, Roth Tran, and Watugala (2023)

$$\text{Stock VRP}_{s,t+1} = \gamma_s + \gamma_t + b_v \cdot \text{WVOL}_{c,t} + \phi \cdot X_{s,t} + \epsilon_{s,t+1} \tag{2.7}$$

Stock $\text{VRP}_{s,t}$ is the credit spread during month t of stock s. Control variables include the stock variance risk premia. We also include individual firm and time (year quarter) fixed effects. Additionally we control for the forecasted value of the end of month (seasonal strip) futures contract payoff for county c at time t ($XDD_{c,t}/XDDss_{c,t}$).[15]

Firms reveal some differing levels and different types of exposure they have to climate change via reportings and in company earnings. 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 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 ($\text{CCOpportunity}^{Risk}$). Additionally we control for the level economic uncertainty in our regressions measured by the EPU_{t-1} (and EJS $\text{SEPU}_{s,t-1}$) the monthly measured state level uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time t respectively.

[15]We find similar results when using the $XDD_{c,t-1}/XDDss_{c,t-1}$ as the forecasted value of the end of month (seasonal strip) futures contract payoff instead of payoff uncertainty.

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

3 Main Results

3.1 Municipal Bond Main Results

Our test of hypothesis 1 is the impact of the four weather volatility uncertainty measures (WVOL) and their impact on the cross-section of municipal bonds whose counties are proximately close to those cities with corresponding weather derivatives. Table 7 displays the results of the estimation of equation 2.5 with the dependent variable being the municipal bond credit spreads regressed individually on each of the four weather volatility uncertainty measures displayed in columns (1) to (4) respectively. Each of the four 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, and log-bond turnover, $XDD_{c,t-1}/XDDss_{c,t-1}$) are lagged by one time period.[17] Regression in Column (1) controls for the forecasted value of the end of month futures contract payoff for county c at time $t-1$ (i.e. $XDD_{c,t-1}$) whereas the regressions in Columns (2) to (4) control for the forecasted value of the end of seasonal strip futures contract payoff for county c at time $t-1$ (i.e. $XDDss_{c,t-1}$).

We find that both the WRVOL and WRVOLss both positively predicts future credit spreads, hence a higher temperature futures volatility is associated with a increasing credit spread for both monthly and seasonal contracts with coefficients (t-statistic) of $0.4e-3$ (7.41) and $4e-3$ (7.31) respectively (both statistically significant at the 1% level). The WIVOLss and WVRPss both negatively predicts future municipal bond credit spreads with coefficients (t-statistic) of $-1.5e-3$ (-5.48) and $-1.8e-3$ (-7.64) respectively (both statistically significant at the 1% level). Hence hedging a higher temperature futures volatility is associated with a decreasing municipal bond credit spread as indicated by the negative weather variance risk premia.

[17] 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 and standard errors are computed by clustering at the municipal bond individual CUSIP level.

INSERT TABLE 7 HERE

Table 8 re-estimates the monthly panel regression equation 2.5 for the subsets of municipal bonds with time to maturity less (greater) than 15 years in Panel A (B) respectively. In both panels A and B both of WRVOL and WRVOLss, (WIVOLss, and WVRPss) positively (negatively) predicts future municipal bond credit spreads as in the main results in Table 7. All of the coefficients (with the exception of WRVOL in the subset of time to maturity greater than 15 years). Both of WRVOL and WRVOLss have larger positive coefficients on the impact of municipal bond credit spreads with shorter term to maturity than longer term to maturity indicating that more weather uncertainties in the shorter term than longer term. Both of WIVOLss, and WVRPss have larger negative coefficients on the impact of municipal bond credit spreads with longer term to maturity than shorter term to maturity indicating the effectiveness of weather futures in hedging decreases credit spreads more for longer term than shorter term bonds.

INSERT TABLE 8 HERE

3.2 Corporate Bond Main Results

Our test of hypothesis 2 is the impact of the four weather volatility uncertainty measures ($\text{WVOL}_{s,t}$) and their impact on the cross-section of corporate bonds whose counties are proximately close to those cities with corresponding weather derivatives. Table 11 displays the results of the estimation of equation 2.6 with the dependent variable being the corporate bond credit spreads regressed individually on each of the four weather volatility uncertainty measures displayed in columns (1) to (4) respectively. Each of the four 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. As in the municipal bond regressions, all control variables (bond's time to maturity, credit rating, and log-bond turnover, $XDD_{c,t-1}/XDDss_{c,t-1}$) are lagged by one month period.[18] Regression in Column (1) controls for the forecasted value of the end of month futures contract whereas the regressions in Columns (2) to (4) control for the forecasted value of the end of seasonal strip futures contract payoff.

We find that the WRVOL (WRVOLss) negatively (positively) predicts future corporate credit spreads, hence a higher monthly temperature futures volatility is associated with a decreasing (increasing) corporate credit spreads for both monthly and seasonal contracts with coefficients (t-statistic) of $-0.2e-3$ (-1.64) and 0.01 (3.91) respectively. The WIVOLss and WVRPss both negatively predicts future corporate credit spreads with coefficients (t-statistic) of $-2.1e-3$ (-2.73) and $-4.5e-3$ (-6.16) respectively (both statistically significant at the 1% level). Hence hedging a higher temperature futures volatility is associated with a decreasing corporate bond credit spread as indicated by the negative weather variance risk premia.

INSERT TABLE 11 HERE

Table 11 Panel B and C re-estimates the monthly panel regression equation 2.6 (shown in Panel A) for the subsets of corporate bonds with time to maturity less (greater) than 15 years in Panel B (C) respectively. In both panels B and C each of WRVOL, WIVOLss, and WVRPss all negatively predicts future corporate credit spreads, (and WRVOLss positively predicts future corporate credit spreads) as in the main results in Panel A.

WRVOLss has larger positive coefficients on the impact of corporate bond credit spreads with shorter term to maturity than longer term to maturity indicating that more weather uncertainties in the shorter term than longer term. Both of WIVOLss, and WVRPss have larger negative coefficients on the impact of corporate credit spreads with shorter term to maturity than longer term to maturity indicating the effectiveness of weather futures in hedging decreases corporate credit spreads more for shorter term than longer term bonds.

[18]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.

INSERT TABLE 12 HERE

Table 12 Panel A and B re-estimates the monthly panel regression equation 2.6 (shown in Table 11 Panel A) for the subsets of corporate bonds with investment grade (high yield) credit rating in Panel B (C) respectively.

3.3 Stock VRP Main Results

Our test of hypothesis 3 is the impact of the four weather volatility uncertainty measures ($\text{WVOL}_{s,t}$) and their impact on the cross-section of firm level stock variance risk premia whose location are within 100km to those cities with corresponding weather derivatives. Table 9 displays the results of the estimation of equation 2.7 with the dependent variable being the municipal bond credit spreads regressed individually on each of the four weather volatility uncertainty measures displayed in columns (1) to (4) respectively.

We find that the WRVOL (WRVOLss) negatively (positively) predicts future firm level stock variance risk premia, hence a higher monthly temperature futures volatility is associated with a decreasing (increasing) firm level stock variance risk premia for both monthly and seasonal contracts with coefficients (t-statistic) of $-2.3e-3$ (-2.47) and 0.05 (2.66) respectively. The WIVOLss and WVRPss both negatively predicts future firm level stock variance risk premia with coefficients (t-statistic) of -0.01 (-1.55) and -0.02 (-2.72) respectively. Hence a higher temperature futures hedging volatility is associated with a decreasing firm level stock variance risk premia.

INSERT TABLE 9 HERE

Table 9 panels B and C shows the results of panel regression equation 2.7 with the additional controls for the monthly measured state level uncertainty measure of Baker et al. (2022) (EPU_t) and Elkhami, Jo, and Salerno (2023b) (EJS $\text{SEPU}_{s,t}$) respectively. 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 9.

4 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, C) presents the results of panel regression equation 2.7 estimation when controlling for the three different measures of climate change exposure. Individually adding the measures of climate change exposure does not change any of the original results of Table 9.

INSERT TABLE 10 HERE

Table 13 panels A and B show the results of estimating panel regression equation 2.6 with the additional controls for $\text{EPU}_{s,t-1}$ (EJS $\text{SEPU}_{s,t-1}$) the monthly measured state level uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$ respectively. 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 12.

INSERT TABLE 13 HERE

Table 14 (panels A, B, 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 change any of the original results of Table 11.

INSERT TABLE 14 HERE

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 munuicipal 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.

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Table 1 CME Weather Derivatives Data Details

Options		Futures	
Option Series	CME Code	Futures Series	CME Code
Chicago HDD Monthly Options	12	Chicago HDD Monthly Futures	$H2$
Dallas HDD Monthly Options	15	Dallas HDD Monthly Futures	$H5$
New York HDD Monthly Options	2#	New York HDD Monthly Futures	$H4$
Amsterdam HDD Monthly Options	$O2$	Amsterdam HDD Monthly Futures	$D2$
New York HDD NOV Seasonal Strip Options	$14X$	New York HDD NOV Seasonal Strip Futures	$H4X$
Dallas HDD NOV Seasonal Strip Options	$15X$	Dallas HDD NOV Seasonal Strip Futures	$H5X$
Amsterdam HDD NOV Monthly Strip Options	$O2X$	Amsterdam HDD NOV Monthly Strip Futures	$D2X$
Minneapolis HDD NOV Seasonal Strip Options	$34X$	Minneapolis HDD NOV Seasonal Strip Futures	HQX
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	$K2K$
New York CDD MAY Seasonal Strip Options	$24K$	New York CDD MAY Seasonal Strip Futures	$K4K$
Dallas CDD May Seasonal Strip Options	$25K$	Dallas CDD MAY Seasonal Strip Futures	$K5K$

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 2 Seasonal Strips Futures Options Summary Statistics

State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
All Seasonal Strip Options									
Implied Volatility	52120	0.37	0.32	0.24	0.83	0.13	0.17	0.51	0.77
Open Interest	52120	903.39	750.00	782.87	1.79	250.00	250.00	1250.00	2000.00
d2mat	52120	100.2	95.00	62.63	0.44	20.00	49.00	146.00	185.00
TTM	52120	0.28	0.26	0.17	0.44	0.06	0.14	0.41	0.51
Chicago HDD NOV Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	7110	0.43	0.41	0.3	0.23	0.1	0.12	0.7	0.84
Open Interest	7110	810.32	500.00	795.78	1.76	50.00	250.00	1000.00	1750.00
d2mat	7110	101.87	99.00	60.56	0.39	24.00	53.00	145.00	184.00
TTM	7110	0.28	0.28	0.17	0.39	0.07	0.15	0.4	0.51
New York HDD NOV Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	9953	0.4	0.4	0.25	0.41	0.12	0.14	0.59	0.77
Open Interest	9953	1025.59	750.00	906.57	1.91	250.00	250.00	1250.00	2250.00
d2mat	9953	112.95	105.00	72.78	0.59	24.00	53.00	163.00	214.00
TTM	9953	0.31	0.29	0.2	0.59	0.07	0.15	0.45	0.59
Dallas HDD NOV Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	5292	0.41	0.38	0.2	0.76	0.2	0.25	0.52	0.71
Open Interest	5292	705.93	500.00	616.21	1.83	250.00	250.00	750.00	1500.00
d2mat	5292	102.7	99.00	61.38	0.28	24.00	51.00	150.5	187.00
TTM	5292	0.29	0.28	0.17	0.28	0.07	0.14	0.42	0.52
Chicago CDD MAY Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	5098	0.34	0.32	0.12	1.82	0.22	0.27	0.38	0.46
Open Interest	5098	1153.06	1050.00	715.48	0.8	250.00	500.00	1500.00	2000.00
d2mat	5098	93.09	86.00	59.8	0.38	17.00	43.00	139.00	176.00
TTM	5098	0.26	0.24	0.17	0.38	0.05	0.12	0.39	0.49
New York CDD MAY Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	9227	0.27	0.24	0.12	1.85	0.15	0.19	0.32	0.41
Open Interest	9227	969.41	500.00	975.14	1.6	250.00	250.00	1250.00	2500.00
d2mat	9227	92.59	87.00	57.87	0.29	17.00	44.00	139.00	173.00
TTM	9227	0.26	0.24	0.16	0.29	0.05	0.12	0.39	0.48
Dallas CDD May Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	9687	0.28	0.26	0.15	1.16	0.13	0.15	0.38	0.48
Open Interest	9687	877.52	750.00	634.97	1.23	250.00	500.00	1250.00	1750.00
d2mat	9687	94.23	92.00	58.15	0.25	17.00	45.00	141.00	174.00
TTM	9687	0.26	0.26	0.16	0.25	0.05	0.13	0.39	0.48
Minneapolis HDD NOV Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	5753	0.59	0.7	0.3	−0.53	0.12	0.26	0.84	0.91
Open Interest	5753	705.11	500.00	408.2	1.01	250.00	422.00	1000.00	1250.00
d2mat	5753	102.32	98.00	60.45	0.23	24.00	53.00	150.00	189.00
TTM	5753	0.28	0.27	0.17	0.23	0.07	0.15	0.42	0.53

Note: This table 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 mentioned in Table 1.

Table 3 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	39405	$-0.4e-3$	0.00	0.06	0.55	-0.04	-0.01	0.01	0.03
CA	4451	$-1.4e-3$	0.00	0.06	-0.91	-0.04	-0.01	0.01	0.04
GA	5123	$0e-3$	0.00	0.05	0.9	-0.04	-0.01	0.01	0.04
IL	5077	$-0.4e-3$	0.00	0.06	-0.07	-0.04	-0.01	0.01	0.04
MN	4478	$0.8e-3$	0.00	0.07	1.7	-0.04	-0.01	0.01	0.03
NV	4854	$-1.3e-3$	0.00	0.06	0.56	-0.03	-0.01	0.01	0.03
NY	5162	$-0.2e-3$	0.00	0.06	0.38	-0.03	-0.01	0.01	0.03
OH	5119	$-0.1e-3$	0.00	0.05	0.39	-0.04	-0.01	0.01	0.04
TX	5141	$-0.7e-3$	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	1637	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 4 Municipal Bonds Summary Statistics

State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
All States									
yield vw	1823869	0.02	0.02	0.01	0.51	0.01	0.02	0.03	0.04
TTM	1823869	13.18	12.02	6.93	0.53	4.93	7.7	17.83	23.78
Amt. Out.	1823869	56272704.64	19770000.00	143147241.00	9.74	1465000.00	5420000.00	51675000.00	124145000.00
Muni. CS.	1823869	$3.4e-3$	$1.7e-3$	0.01	1.19	-0.01	$-2.6e-3$	0.01	0.02
California									
yield vw	453909	0.02	0.02	0.01	0.52	0.01	0.01	0.03	0.04
TTM	453909	12.59	11.28	6.83	0.72	4.79	7.41	16.58	23.41
Amt. Out.	453909	77546285.78	34675000.00	212631965.00	9.24	3410000.00	9815000.00	77840000.00	134570000.00
Muni. CS.	453909	$0.7e-3$	$-0.3e-3$	0.01	1.06	-0.01	$-4.1e-3$	$4.1e-3$	0.01
Georgia									
yield vw	115270	0.02	0.02	0.01	0.19	0.01	0.01	0.03	0.04
TTM	115270	12.6	11.39	6.68	0.62	4.84	7.35	16.95	22.52
Amt. Out.	115270	29969858.75	17025000.00	55206324.81	5.72	2160000.00	5000000.00	32510000.00	58420000.00
Muni. CS.	115270	$1.5e-3$	$0.7e-3$	0.01	0.5	-0.01	$-3.2e-3$	0.01	0.01
Illinois									
yield vw	304445	0.03	0.03	0.02	0.17	0.01	0.02	0.04	0.06
TTM	304445	13.63	12.94	6.8	0.36	5.11	8.11	18.59	23.32
Amt. Out.	304445	63057898.86	15000000.00	128033437.00	3.58	1030000.00	3450000.00	51365000.00	169505000.00
Muni. CS.	304445	0.01	0.01	0.01	0.54	$-2.3e-3$	$2.1e-3$	0.02	0.03
Minnesota									
yield vw	44571	0.02	0.02	0.01	0.36	0.01	0.01	0.03	0.03
TTM	44571	10.67	9.66	5.65	0.89	4.2	6.49	13.98	18.19
Amt. Out.	44571	7274898.18	3130000.00	11316215.71	2.6	365000.00	995000.00	7370000.00	19985000.00
Muni. CS.	44571	$1.8e-3$	$0.6e-3$	0.01	1.66	$-5e-3$	$-2.6e-3$	$4.6e-3$	0.01
New York									
yield vw	638503	0.02	0.02	0.01	0.2	0.01	0.02	0.03	0.04
TTM	638503	14.05	13.1	7.17	0.36	5.18	8.27	19.33	24.78
Amt. Out.	638503	63082160.67	27965000.00	124455150.00	6.16	3630000.00	12020000.00	59775000.00	150000000.00
Muni. CS.	638503	$2.6e-3$	$1.5e-3$	0.01	0.92	-0.01	$-2.8e-3$	0.01	0.01
Ohio									
yield vw	43532	0.02	0.02	0.01	0.14	0.01	0.02	0.03	0.04
TTM	43532	12.49	11.05	6.81	0.69	4.75	7.2	16.85	23.05
Amt. Out.	43532	9523497.68	4750000.00	16527040.82	5.09	680000.00	1635000.00	10000000.00	21120000.00
Muni. CS.	43532	$2.9e-3$	$2.2e-3$	0.01	0.58	$-4.8e-3$	$-1.8e-3$	0.01	0.01
Texas									
yield vw	223639	0.02	0.02	0.01	0.21	0.01	0.01	0.03	0.04
TTM	223639	12.19	10.88	6.63	0.73	4.65	7.1	16.24	22.18
Amt. Out.	223639	16838841.43	4415000.00	56852061.87	8.25	630000.00	1495000.00	13470000.00	28905000.00
Muni. CS.	223639	$1.9e-3$	$1.2e-3$	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 5 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	229367	0.06	0.05	0.07	2.72	0.02	0.03	0.08	0.12
stock VRP	184602	0.01	0.01	0.17	-0.75	-0.11	-0.04	0.05	0.12
EDF	329828	0.08	$0e-3$	0.2	3.12	$0e-3$	$0e-3$	0.01	0.26
Asset Volatility (EDF)	331018	0.48	0.39	0.34	2.69	0.19	0.26	0.59	0.9
RVOL ssFret	75192	0.1	0.09	0.06	1.12	0.04	0.06	0.12	0.18
RVOL Fret	343597	0.59	0.43	0.47	1.48	0.19	0.28	0.74	1.33
WIVOL	105636	0.44	0.4	0.2	0.57	0.18	0.29	0.58	0.74
WVRP	51981	0.29	0.27	0.22	0.67	0.04	0.09	0.4	0.61
sum XDDi	271110	406.63	352.97	290.28	1.13	84.77	199.06	536.98	825.76
sum CDDi	135488	290.77	269.19	184.87	0.46	55.18	140.96	426.55	533.54
sum HDDi	135622	522.37	462.37	327.87	0.77	153.32	270.41	711.04	986.21
sum XDDssi	263247	2585.98	2190.11	1517.41	1.19	1056.95	1600.45	3197.16	4880.6
Corp Bond Ret (EOM)	417123	0.01	$4.1e-3$	0.04	3.61	-0.02	$-4.2e-3$	0.02	0.03
CORP TMT	417123	9.29	6.21	8.17	1.19	1.9	3.34	11.92	24.31
DURATION	415978	6.17	5.07	4.05	0.91	1.81	3.01	8.22	12.71
Corp Bond Ret (L5M)	324156	0.01	$3.8e-3$	0.03	3.79	-0.02	$-3.7e-3$	0.01	0.03
Corp Rating	396681	7.92	7.00	3.16	0.96	5.00	6.00	9.00	13.00
Corp Bid Ask Spread	374208	0.01	$4.1e-3$	0.01	30.81	$1.1e-3$	$2.2e-3$	0.01	0.01
Corp CS	268652	0.02	0.01	0.03	9.9	$3.1e-3$	0.01	0.02	0.04
Corp Amount Out.	417105	593030.76	400000.00	657336.31	2.94	40000.00	200000.00	750000.00	1299750.00

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. $\text{WRVOL}_{c,t}$ ($\text{WRVOLss}_{c,t}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time t. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monthly average option implied volatility for county c at time t and $\text{WVRPss}_{c,t}$ is the difference between the $\text{WIVOLss}_{c,t}$ and $\text{WRVOLss}_{c,t}$ for county c at time t

Table 6 : Correlations

	Correlations												
Variable Names	$WRVOLss$	$WRVOL$	$WVRP$	XDD	$XDDss$	CS	TMT	$RATING$	$log(AO/Vol)$	EPU	$log(OIss)$	$log(optOIss)$	$SEPU$
WRVOLss	1.00	0.34	−0.47	−0.03	−0.13	−0.02	0.01	0.00	−0.01	−0.01	0.14	0.12	−0.11
WRVOL	0.34	1.00	−0.28	−0.45	−0.41	0.01	0.00	0.00	−0.01	−0.12	0.06	0.00	−0.04
WVRP	−0.47	−0.28	1.00	0.21	0.27	0.06	0.01	0.07	0.02	0.2	−0.51	0.15	0.2
XDD	−0.03	−0.45	0.21	1.00	0.91	0.01	0.01	−0.02	0.02	0.19	−0.18	0.21	0.07
XDDss	−0.13	−0.41	0.27	0.91	1.00	0.01	0.01	−0.01	0.01	0.21	−0.22	0.25	0.1
CS	−0.02	0.01	0.06	0.01	0.01	1.00	−0.02	0.4	−0.03	0.16	0.07	0.05	0.12
TMT	0.01	0.00	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	0.00	0.07	−0.02	−0.01	0.4	−0.03	1.00	−0.12	−0.06	−0.13	−0.04	0.02
log(AO/Vol)	−0.01	−0.01	0.02	0.02	0.01	−0.03	0.11	−0.12	1.00	−0.02	0.00	−0.04	−0.03
EPU	−0.01	−0.12	0.2	0.19	0.21	0.16	−0.02	−0.06	−0.02	1.00	0.1	0.1	0.42
log(OIss)	0.14	0.06	−0.51	−0.18	−0.22	0.07	−0.04	−0.13	0.00	0.1	1.00	−0.17	−0.11
log(optOIss)	0.12	0.00	0.15	0.21	0.25	0.05	0.00	−0.04	−0.04	0.1	−0.17	1.00	0.05
SEPU	−0.11	−0.04	0.2	0.07	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 accounting quality measures from Table . The sample period is quarterly observations from January 1997 to December 2017.

Table 7 Municipal Bond Credit Spreads and WVRP

Panel A: Full Sample and control for EPU				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.4e-3$			
	(7.41)			
$\text{WIVOLss}_{c,t-1}$		$-1.5e-3$		
		(-5.84)		
$\text{WRVOLss}_{c,t-1}$			$4e-3$	
			(7.31)	
$\text{WVRPss}_{c,t-1}$				$-1.8e-3$
				(-7.64)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(13.14)	(11.48)	(10.19)	(12.07)
TTM_{t-1}	$0.2e-3$	$0.2e-3$	$0.1e-3$	$0.2e-3$
	(2.16)	(2.08)	(1.67)	(2.2)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.1e-3$	$0.1e-3$	$0.1e-3$	$0.1e-3$
	(3.04)	(3)	(2.59)	(2.96)
EPU_{t-1}	$0.1e-3$	0.00	$0.1e-3$	0.00
	(2.47)	(-0.14)	(2.26)	(-0.71)
R^2	90.77	90.53	98.45	90.54
N obs	51,350	54,830	158,486	54,830
Fixed Effects				
Bond CUSIP	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond CUSIP	Y	Y	Y	Y

Panel B: Full Sample and control for EJS SEPU				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.4e-3$			
	(7.7)			
$\text{WIVOLss}_{c,t-1}$		$-2e-3$		
		(-7.75)		
$\text{WRVOLss}_{c,t-1}$			$4.1e-3$	
			(6.82)	
$\text{WVRPss}_{c,t-1}$				$-2.1e-3$
				(-9.04)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(12.84)	(11.98)	(10.76)	(12.37)
TTM_{t-1}	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.2e-3$
	(2.34)	(2.57)	(1.86)	(2.58)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.1e-3$	$0.1e-3$	$0.1e-3$	$0.1e-3$
	(3.01)	(2.93)	(3.01)	(2.91)
EPU_{t-1}	$-0.1e-3$	$-0.4e-3$	$-0.1e-3$	$-0.4e-3$
	(-1.71)	(-11.96)	(-2.08)	(-11.13)
R^2	90.77	90.55	90.53	90.56
N obs	51,350	54,830	54,830	54,830
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	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 $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time $t-1$. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time $t-1$ and $\text{WVRPss}_{c,t-1}$ is the difference between the $\text{WIVOLss}_{c,t-1}$ and $\text{WRVOLss}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}/XDDss_{c,t-1}$ is the forecasted value of the end of 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 $\log(\text{AmtOut/DollVolume})_{i,t-1}$ 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. Panel A (B) reports the results for the full sample of municipal bonds controlling for the monthly state level uncertainty measure of EPU_{t-1} Baker et al. (2022) (EJS $\text{SEPU}_{s,t-1}$, Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$. T-statistics are presented in parentheses under the coefficients.

Table 8 Municipal Bond Credit Spreads and WVRP

Panel A: $TTM < 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.8e-3$			
	(10.85)			
$\text{WIVOLss}_{c,t-1}$		$-0.9e-3$		
		(-3.05)		
$\text{WRVOLss}_{c,t-1}$			0.01	
			(8.94)	
$\text{WVRPss}_{c,t-1}$				$-1.3e-3$
				(-5.02)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(11.37)	(8.53)	(7.27)	(9.29)
TTM	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.2e-3$
	(2.06)	(2.08)	(1.95)	(2.2)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.1e-3$	0.00	0.00	0.00
	(2.72)	(2.63)	(2.64)	(2.61)
EPU_{t-1}	0.00	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-0.96)	(-2.32)	(-1.99)	(-2.8)
R^2	93.04	92.68	92.7	92.69
N obs	30,253	32,732	32,732	32,732
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel B: $TTM > 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.1e-3$			
	(1.29)			
$\text{WIVOLss}_{c,t-1}$		$-1.4e-3$		
		(-3.55)		
$\text{WRVOLss}_{c,t-1}$			$4.3e-3$	
			(5.1)	
$\text{WVRPss}_{c,t-1}$				$-1.8e-3$
				(-4.49)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(6.74)	(6.97)	(7.02)	(7.26)
TTM	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.2e-3$
	(1.1)	(1.19)	(1.06)	(1.29)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.1e-3$	$0.1e-3$	$0.1e-3$	$0.1e-3$
	(1.51)	(1.56)	(1.54)	(1.51)
EPU_{t-1}	$0.2e-3$	$0.1e-3$	$0.1e-3$	$0.1e-3$
	(3.65)	(2.13)	(2.32)	(1.7)
R^2	88.79	88.66	88.65	88.67
N obs	21,097	22,098	22,098	22,098
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	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 $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time $t-1$. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time $t-1$ and $\text{WVRPss}_{c,t-1}$ is the difference between the $\text{WIVOLss}_{c,t-1}$ and $\text{WRVOLss}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}/XDDss_{c,t-1}$ is the forecasted value of the end of 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 $\log(\text{AmtOut/DollVolume})_{i,t-1}$ 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. Panel A (B) reports the results for the full sample of municipal bonds controlling for the monthly state level uncertainty measure of EPU_{t-1} Baker et al. (2022) (EJS $\text{SEPU}_{s,t-1}$, Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$. T-statistics are presented in parentheses under the coefficients.

Table 9 Stock VRP and the WVRP

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-2.3e-3$			
	(-2.47)			
$\text{WIVOLss}_{c,t}$		-0.01		
		(-1.55)		
$\text{WRVOLss}_{c,t}$			0.05	
			(2.66)	
$\text{WVRPss}_{c,t}$				-0.02
				(-2.72)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.94)	(-1.72)	(-0.87)	(0.27)
Stock VRP_t	0.67	0.61	0.68	0.54
	(33.21)	(14.53)	(24.8)	(16.08)
R^2	68.72	89.66	90.34	95.31
N obs	57,784	22,815	16,774	10,987
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	Y	Y	Y	Y

Panel B: Full Sample and control for EPU				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-2.2e-3$			
	(-2.33)			
$\text{WIVOLss}_{c,t}$		-0.01		
		(-1.44)		
$\text{WRVOLss}_{c,t}$			0.05	
			(2.83)	
$\text{WVRPss}_{c,t}$				-0.02
				(-2.71)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-3.14)	(-1.87)	(-1.28)	(0.26)
Stock VRP_t	0.67	0.61	0.68	0.54
	(33.18)	(14.52)	(24.75)	(16.07)
EPU_t	$2.8e-3$	$2.7e-3$	0.01	$0.2e-3$
	(2.06)	(1.34)	(1.87)	(0.06)
R^2	68.73	89.66	90.34	95.31
N obs	57,784	22,815	16,774	10,987
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	Y	Y	Y	Y

Panel C: Full Sample and control for EJS SEPU				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-2.3e-3$			
	(-2.46)			
$\text{WIVOLss}_{c,t}$		-0.01		
		(-1.54)		
$\text{WRVOLss}_{c,t}$			0.04	
			(2.24)	
$\text{WVRPss}_{c,t}$				-0.02
				(-2.8)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.85)	(-1.73)	(-0.61)	(0.32)
Stock VRP_t	0.67	0.61	0.68	0.54
	(33.21)	(14.53)	(24.82)	(16.09)
EJS SEPU_t	$-1.5e-3$	$0.8e-3$	-0.01	-0.01
	(-1.33)	(0.47)	(-3.14)	(-2.27)
R^2	68.72	89.66	90.34	95.31
N obs	57,784	22,815	16,774	10,987
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	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. $\text{WRVOL}_{c,t}$ ($\text{WRVOLss}_{c,t}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time t. Similarly $\text{WIVOLss}_{c,t}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time t and $\text{WVRPss}_{c,t}$ is the difference between the $\text{WIVOLss}_{c,t}$ and $\text{WRVOLss}_{c,t}$. $XDD_{c,t}/XDDss_{c,t}$ is the forecasted value of the end of 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 10 Robustness: Stock VRP and the WVRP

Panel A: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\mathrm{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\mathrm{WIVOLss}_{c,t-1}$		-0.01		
		(-1.59)		
$\mathrm{WRVOLss}_{c,t-1}$			0.05	
			(2.83)	
$\mathrm{WVRPss}_{c,t-1}$				-0.02
				(-2.93)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.78)	(-1.61)	(-1.01)	(-0.05)
Stock VRP_t	0.66	0.6	0.67	0.5
	(28.3)	(11.08)	(20.57)	(12.51)
EPU_t	$3.6e-3$	$3.8e-3$	0.01	$2.4e-3$
	(2.68)	(1.94)	(2.24)	(0.8)
cc risk ew_t	0.08	5.49	1.64	2.17
	(0.04)	(1.75)	(0.52)	(0.7)
R^2	73.05	91.81	92.16	96.36
N obs	53,924	21,156	15,189	9,976
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	Y	Y	Y	Y

Panel B: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\mathrm{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\mathrm{WIVOLss}_{c,t-1}$		-0.01		
		(-1.6)		
$\mathrm{WRVOLss}_{c,t-1}$			0.05	
			(2.83)	
$\mathrm{WVRPss}_{c,t-1}$				-0.02
				(-2.9)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.79)	(-1.62)	(-1.01)	(-0.04)
Stock VRP_t	0.66	0.6	0.67	0.5
	(28.3)	(11.08)	(20.57)	(12.52)
EPU_t	$3.6e-3$	$3.8e-3$	0.01	$2.4e-3$
	(2.67)	(1.96)	(2.24)	(0.8)
cc expo ew_t	-0.19	-0.48	1.64	-1
	(-0.62)	(-0.87)	(0.52)	(-0.94)
R^2	73.05	91.81	92.16	96.36
N obs	53,924	21,156	15,189	9,976
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	Y	Y	Y	Y

Panel C: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\mathrm{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\mathrm{WIVOLss}_{c,t-1}$		-0.01		
		(-1.6)		
$\mathrm{WRVOLss}_{c,t-1}$			0.05	
			(2.84)	
$\mathrm{WVRPss}_{c,t-1}$				-0.02
				(-2.89)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.78)	(-1.62)	(-1.01)	(-0.05)
Stock VRP_t	0.66	0.6	0.67	0.5
	(28.31)	(11.08)	(20.55)	(12.5)
EPU_t	$3.6e-3$	$3.8e-3$	0.01	$2.4e-3$
	(2.68)	(1.96)	(2.23)	(0.81)
op risk ew_t	-6.5	-5.35	-29.22	-34.85
	(-1.21)	(-0.65)	(-2.7)	(-2.5)
R^2	73.05	91.81	92.16	96.36
N obs	53,924	21,156	15,189	9,976
Fixed Effects				
Firm	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Firm	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. $\mathrm{WRVOL}_{c,t}$ ($\mathrm{WRVOLss}_{c,t}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time t. Similarly $\mathrm{WIVOLss}_{c,t}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time t and $\mathrm{WVRPss}_{c,t}$ is the difference between the $\mathrm{WIVOLss}_{c,t}$ and $\mathrm{WRVOLss}_{c,t}$ for county c at time t. $XDD_{c,t}/XDDss_{c,t}$ is the forecasted value of the end of 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 11 Corporate Credit Spreads and WVRP

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-1.64)			
$\text{WIVOLss}_{c,t-1}$		$-2.1e-3$		
		(-2.73)		
$\text{WRVOLss}_{c,t-1}$			0.01	
			(3.91)	
$\text{WVRPss}_{c,t-1}$				$-4.5e-3$
				(-6.16)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-1.76)	(3.16)	(2.6)	(0.75)
TTM_{t-1}	$0.2e-3$	0.00	$1.1e-3$	$2.5e-3$
	(0.68)	(0.09)	(1.69)	(5.01)
$Rating_{t-1}$	$3.7e-3$	$3.2e-3$	0.01	$3.2e-3$
	(8.75)	(5.78)	(7.75)	(7.27)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.2e-3$	$-0.1e-3$	$-0.2e-3$	$-0.2e-3$
	(2.32)	(-1.97)	(-1.46)	(-3.66)
R^2	70.27	94.42	86.43	96.51
N obs	165,747	60,716	44,136	42,150
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel B: $TTM < 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-1.36)			
$\text{WIVOLss}_{c,t-1}$		$-2.9e-3$		
		(-3.23)		
$\text{WRVOLss}_{c,t-1}$			$4.4e-3$	
			(1.71)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-5.82)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-1.5)	(-0.11)	(-0.18)	(0.98)
TTM_{t-1}	$0.4e-3$	0.00	$1.3e-3$	$2.8e-3$
	(0.92)	(0.05)	(2.04)	(4.07)
$Rating_{t-1}$	$4.5e-3$	$3.8e-3$	0.01	$3.8e-3$
	(8.44)	(5.51)	(7.8)	(7.16)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.2e-3$	$-0.1e-3$	$0.1e-3$	$-0.2e-3$
	(2.65)	(-2.1)	(0.96)	(-3.13)
EPU_{t-1}	$0.2e-3$	$-0.5e-3$	$0.5e-3$	$-0.2e-3$
	(0.57)	(-3.06)	(1.23)	(-1.05)
R^2	63.94	92.52	80.3	96.54
N obs	126,209	64,178	47,992	32,333
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel C: $TTM > 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-2.18)			
$\text{WIVOLss}_{c,t-1}$		$-0.2e-3$		
		(-0.32)		
$\text{WRVOLss}_{c,t-1}$			$4.1e-3$	
			(2.18)	
$\text{WVRPss}_{c,t-1}$				$-4e-3$
				(-4.4)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.83)	(-2.23)	(-0.6)	(-0.89)
TTM_{t-1}	$-0.5e-3$	$-0.2e-3$	$-0.2e-3$	$1.1e-3$
	(-2.04)	(-0.32)	(-0.55)	(2.1)
$Rating_{t-1}$	$1.5e-3$	$1e-3$	$1.8e-3$	$1e-3$
	(5.15)	(3.36)	(3.74)	(3.25)
$\log(\text{AmtOut/DollVolume})_{t-1}$	0.00	$-0.1e-3$	$-0.2e-3$	$-0.2e-3$
	(0.12)	(-1.4)	(-1.48)	(-2.27)
EPU_{t-1}	$0.5e-3$	$0.1e-3$	$0.6e-3$	$0.8e-3$
	(3.28)	(0.66)	(1.85)	(3.82)
R^2	83.1	94.08	91.18	97.8
N obs	39,538	20,694	14,115	9,817
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	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 $t-1$. of county c at time $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time $t-1$. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monthly average option implied volatility for county c at time $t-1$ and $\text{WVRPss}_{c,t-1}$ is the difference between the $\text{WIVOLss}_{c,t-1}$ and $\text{WRVOLss}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}/XDDss_{c,t-1}$ is the forecasted value of the end of 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 $t-1$. EPU_{t-1} (EJS $\text{SEPU}_{s,t-1}$) is the monthly measured state level uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$. 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 12 Corporate Credit Spreads and WVRP: Subset IG and HY

Panel A: IG Corporate Bonds				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-3.45)			
$\text{WIVOLss}_{c,t-1}$		$0e-3$		
		(0.14)		
$\text{WRVOLss}_{c,t-1}$			$0e-3$	
			(0.01)	
$\text{WVRPss}_{c,t-1}$				$-2.7e-3$
				(-5.52)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-4.55)	(-3.76)	(-1.14)	(0.33)
TTM_{t-1}	0.00	$0.1e-3$	$0.7e-3$	$2e-3$
	(-0.09)	(0.23)	(2.43)	(4.48)
$Rating_{t-1}$	$3.3e-3$	$0.9e-3$	0.01	$1e-3$
	(7.38)	(5.26)	(7.58)	(4.88)
$\log(\text{AmtOut/DollVolume})_{t-1}$	0.00	$-0.1e-3$	$-0.1e-3$	$-0.2e-3$
	(1.12)	(-1.61)	(-1.02)	(-3.44)
EPU_{t-1}	$0.7e-3$	$-0.1e-3$	$0.7e-3$	0.00
	(5.02)	(-1.96)	(2.6)	(0.41)
R^2	66.12	93.89	75.13	96.43
N obs	148, 203	77, 763	56, 719	38, 888
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel B: HY Corporate Bonds				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.5e-3$			
	(-0.67)			
$\text{WIVOLss}_{c,t-1}$		-0.02		
		(-2.57)		
$\text{WRVOLss}_{c,t-1}$			-0.02	
			(-1.34)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-1.68)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-0.2)	(0.21)	(-0.51)	(-1.43)
TTM_{t-1}	$4.6e-3$	-0.01	0.01	$-1.6e-3$
	(0.8)	(-2.21)	(0.99)	(-0.55)
$Rating_{t-1}$	$4.8e-3$	0.01	$1.4e-3$	0.01
	(3.12)	(2.49)	(0.79)	(2.64)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.7e-3$	$-0.1e-3$	$0.4e-3$	$-0.4e-3$
	(1.46)	(-0.3)	(0.74)	(-0.95)
EPU_{t-1}	$2.7e-3$	$-2.5e-3$	0.01	$-0.6e-3$
	(2.14)	(-1.79)	(2.33)	(-0.26)
R^2	61.53	89.47	87.22	96.13
N obs	17, 544	7, 109	5, 388	3, 262
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	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 $t-1$. of county c at time $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time $t-1$. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time $t-1$ and $\text{WVRPss}_{c,t-1}$ is the difference between the $\text{WIVOLss}_{c,t-1}$ and $\text{WRVOLss}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}/XDDss_{c,t-1}$ is the forecasted value of the end of 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 $t-1$. EPU_{t-1} (EJS $\text{SEPU}_{s,t-1}$) is the monthly measured state level uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$. 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 13 Robustness: Corporate Credit Spreads and WVRP

Panel A: Full Sample and control for EPU

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-1.61)			
$\text{WIVOLss}_{c,t-1}$		$-2.1e-3$		
		(-3.03)		
$\text{WRVOLss}_{c,t-1}$			$4.8e-3$	
			(2.33)	
$\text{WVRPss}_{c,t-1}$				$-4.5e-3$
				(-6.02)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.09)	(-0.67)	(-0.58)	(0.73)
TTM_{t-1}	$0.2e-3$	0.00	$1e-3$	$2.5e-3$
	(0.63)	(0.11)	(2.34)	(4.95)
$Rating_{t-1}$	$3.7e-3$	$3.2e-3$	0.01	$3.2e-3$
	(8.76)	(6.02)	(8.04)	(7.27)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.2e-3$	$-0.1e-3$	0.00	$-0.2e-3$
	(2.33)	(-1.67)	(-0.17)	(-3.67)
EPU_{t-1}	$0.3e-3$	$-0.4e-3$	$0.5e-3$	0.00
	(1.31)	(-2.89)	(1.42)	(-0.03)
R^2	64.67	92.4	80.64	96.51
N obs	165,747	84,872	62,107	42,150
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel B: Full Sample and control for EJS SEPU

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-1.67)			
$\text{WIVOLss}_{c,t-1}$		$-2e-3$		
		(-3)		
$\text{WRVOLss}_{c,t-1}$			$3.9e-3$	
			(1.75)	
$\text{WVRPss}_{c,t-1}$				$-4.7e-3$
				(-6.07)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-1.65)	(-1.24)	(0.41)	(0.85)
TTM_{t-1}	$0.2e-3$	0.00	$1e-3$	$2.6e-3$
	(0.7)	(0.1)	(2.48)	(4.97)
$Rating_{t-1}$	$3.7e-3$	$3.2e-3$	0.01	$3.2e-3$
	(8.75)	(6.01)	(8.05)	(7.27)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.2e-3$	$-0.1e-3$	0.00	$-0.2e-3$
	(2.31)	(-1.67)	(-0.18)	(-3.66)
EJS SEPU_{t-1}	$-0.1e-3$	$-0.1e-3$	$-0.8e-3$	$-0.3e-3$
	(-1.02)	(-0.48)	(-2.76)	(-1.59)
R^2	0	92.4	80.65	96.51
N obs	165,747	84,872	62,107	42,150
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	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 $t-1$. of county c at time $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) is the weather futures realized volatility of the monthly (seasonal strip) futures contracts for county c at time $t-1$. Similarly $\text{WIVOLss}_{c,t-1}$ is the weather seasonal strip options monhtly average option implied volatility for county c at time $t-1$ and $\text{WVRPss}_{c,t-1}$ is the difference between the $\text{WIVOLss}_{c,t-1}$ and $\text{WRVOLss}_{c,t-1}$ for county c at time $t-1$. $XDD_{c,t-1}/XDDss_{c,t-1}$ is the forecasted value of the end of 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 $t-1$. EPU_{t-1} ($\text{EJS SEPU}_{s,t-1}$) is the monthly measured state level uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time $t-1$. 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 14 Corporate Credit Spreads with Controls for Risk Reporting

Panel A: Full Sample			
Variable	(1)	(2)	(3)
$\text{WVRPss}_{c,t-1}$	$-4.4e-3$	$-4e-3$	$-4.1e-3$
	(-5.74)	(-5.46)	(-5.4)
$XDD_i/XDDss_i$	0.00	0.00	0.00
	(0.89)	(0.75)	(0.73)
TTM_{t-1}	$2.6e-3$	$2.6e-3$	$2.6e-3$
	(4.95)	(4.95)	(4.91)
$Rating_{t-1}$	$3.3e-3$	$3.3e-3$	$3.3e-3$
	(7.7)	(7.7)	(7.72)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$
	(-3.16)	(-3.19)	(-3.19)
EPU_{t-1}	0.00	0.00	0.00
	(-0.16)	(-0.11)	(-0.08)
cc risk ew_{t-1}	-0.33		
	-1.39		
cc expo ew_{t-1}		-0.46	
		-4.66	
op risk ew_{t-1}			-6.25
			-5.58
R^2	97.87	97.87	97.87
N obs	39,304	39,304	39,304
Fixed Effects			
Bond	Y	Y	Y
Year x Quarter	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y

Note: t-statistics are presented in parentheses under the coefficients where standard errors are computed using clustering by individual firm permno identifier.