Weather Variance Risk Premia

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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 results are 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

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.[1] In other words, investors fear that firms and municipalities operating in local

[1]The weather derivatives market has become increasingly important in hedging against temperature exposure see Robertson (2023).

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, we expect the weather variance risk premia to contemporaneously positively impact the credit spreads of municipalities and local firms and positively predicting the expected bond returns of municipalities and local firms. To test these predictions, we run both contemporaneous (and predictive) regressions to see whether weather derivatives risk premia positively (negatively) contemporaneously (predicts) the bond credit spreads (and thus positive expected returns).

Our principle findings are that our weather variance risk premia is positively contemporaneously priced in the local cross section of stock return variance risk premia, corporate and municipal bond credit spreads. Our results show a higher cost of hedging temperature volatility leads to a higher current cost of hedging equity volatility uncertainty as well as contemporaneously higher localized corporate and municipal 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 stock cash flow uncertainty induced from weather and hence investors demand lower price for corporate and municipal bonds since it is more costly to insure hence current credit spreads increase. 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 imply a higher cost of hedging temperature volatility leads to a expected future lower cost of hedging equity volatility uncertainty as well as lower expected future corporate credit spreads, and localized municipal credit spreads. Our results imply the benefits of hedging temperature volatility on the expected 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 expected real and financial economy.[2] 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 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.[3] 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 (Ginglinger and Moreau (2023) study the impact of physical climate risk in debt structure of firms). 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.[4] Our results imply the benefits of the hedging temperature volatility on the local financial economy. Secondly we contribute to the literature on weather

[2]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.

[3]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).

[4]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.

derivatives, the class of securities whose payoff is contingent on the specific temperature at a particular city.[5] 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 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), 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 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.[6] 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

[5] 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.

[6] 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%.

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.[7] Additionally Drechsler and Yaron (2011) and Drechsler (2013) have shown important ties of the variance risk premia to understanding uncertainty in the macroeconomic and asset pricing puzzles. To this literature our paper contributes a novel variance risk 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).[8] 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), 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.

The rest of this paper is organized as follows: Section 2 outlines the data and empirical

[7] 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 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), Feunou, Jahan-Parvar, and Okou (2018), and Pyun (2019).

[8] Fleming, Kirby, and Ostdiek (2006) find higher comovement of returns and volatilities of commodities during weather sensitive trading periods (also see Hirschleifer and Shumway (2003) and Loughran and Schultz (2004)).

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 (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.

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

where D_t is the number of days in month t, $T_{i,d}$ is the average temperature measured in degrees Fahrenheit of the minimum and maximum temperature for a specific city i on day d. The $\text{HDD}_{i,t}$ ($\text{CDD}_{i,t}$) are 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 $20 \times \text{HDD}_{i,t}$ ($20 \times \text{CDD}_{i,t}$).

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: 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). 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 2019.

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).[9] The monthly futures data set spans from January 2006 to December 2019. Table 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

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

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

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.

INSERT TABLE 4 HERE

Table 4 displays the weather seasonal strip variance risk premia, $\text{WVRPss}_{c,t}$, as well as $\text{WIVOLss}_{c,t}$ and $\text{WRVOLss}_{c,t}$ for each city. The average $\text{WVRPss}_{c,t}$ ranges from 0.27 to 0.59 and ranges from 0.1 (10th percentile) to 0.91 (90th percentile).

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

[10]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).

INSERT TABLE 5 HERE

Table 5 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.[11] 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.

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, 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.

[11] 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.

INSERT TABLE 6 HERE

Table 6 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 7 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.[12] 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 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 as-

[12]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).

sumptions 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).[13] 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).[14] As an additional robustness test, we control for state level economic uncertainty using the measure of Elkhami, Jo, and Salerno (2023b).[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 (CCOpportunity^{Risk}). Additionally we control for the level economic uncertainty in our regressions measured by the EPU$_{t-1}$ (and EJS SEPU$_{s,t-1}$) the monthly measured state level

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

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

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

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

uncertainty measure of Baker et al. (2022) (Elkhami, Jo, and Salerno (2023b)) for state s at time t respectively.

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

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

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

$\text{Muni. Spread}_{b,c,t}$ 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 ($XDD_{c,t}/XDDss_{c,t}$).

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

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

$\text{Corp. Spread}_{b,t}$ 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.[17] 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 ($XDD_{c,t}/XDDss_{c,t}$).

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

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

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 ($XDD_{c,t}/XDDss_{c,t}$).[18]

In order to measure the predictive impact of the weather volatility uncertainty measures ($\text{WVOL}_{s,t}$) in equations 2.5, 2.6, and 2.7, we lag by one month all of the variables on the left hand side of each of the three regression equations.

[17] 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.

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

3 Main Results

3.1 Contemporaneous Results

3.1.1 Municipal Bond Main Results

We test the impact of the four weather volatility uncertainty measures (WVOL) and their contemporaneous impact on the cross-section of municipal bonds credit spreads whose counties are in close proximity to those cities with corresponding weather derivatives. Table 8 displays the results of the estimation of equation 2.5 with the dependent variable being the municipal bond credit spreads regressed individually and contemporaneously on each of the four weather volatility uncertainty measures displayed in columns (1) to (4) respectively with contemporaneous control variables (bond's time to maturity, and log-bond turnover, $XDD_{c,t}/XDDss_{c,t}$). Note that the regression in column (1) controls for the forecasted value of the end of month futures contract payoff for county c at time t (i.e. $XDD_{c,t}$) 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 (i.e. $XDDss_{c,t}$).[19] 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 8 HERE

Panel A of Table 8 shows that the WRVOL, WIVOLss, and WRVOLss are all negatively contemporaneously associated with credit spreads, hence a higher temperature futures volatility is associated with a decreasing credit spread for monthly and seasonal contracts with coefficients (t-statistic) of $-1.4e-3$ (-25.66), $-1.0e-3$ (-2.09), and -0.01 (-29.03) respectively (all statistically significant at the 1% level). The WVRPss is positively contemporaneously associated with municipal bond credit spreads with coefficient (t-statistic)

[19] 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

of 0.01 (20.17) (statistically significant at the 1% level). Our results show a higher cost of hedging temperature volatility leads to contemporaneously higher localized municipal 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 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 8 Panel B (C) respectively 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 both panels B and C both of WRVOL and WRVOLss (WVRPss) are negatively (positively) contemporaneously associated with municipal bond credit spreads as in the main results in Panel A. In particular WVRPss 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 9 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. As in the municipal bond regressions, all control variables (bond's time to maturity, credit rating, and log-bond turnover, $XDD_{c,t}/XDDss_{c,t}$) are contemporaneous.[20] 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.

[20]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. 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.

INSERT TABLE 9 HERE

Panel A of Table 9 shows that the WRVOL, WIVOLss, and WRVOLss are all negatively contemporaneously associated with corporate credit spreads, hence a higher temperature futures volatility is associated with a decreasing credit spread for monthly and seasonal contracts with coefficients (t-statistic) of $-1.1e-3$ (-4.32), -0.01 (-4.16), and -0.01 (-7.3) respectively (all statistically significant at the 1% level). The WVRPss is positively contemporaneously associated with corporate bond credit spreads with coefficient (t-statistic) of 0.01 (5.43) (statistically significant at the 1% level). 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 9 Panel B (C) respectively re-estimates the monthly panel regression equation 2.6 for the subsets of corporate bonds with time to maturity less (greater) than 15 years. In both panels B and C WRVOL, WIVOL, and WRVOLss (WVRPss) are negatively (positively) contemporaneously associated with corporate bond credit spreads as in the main results in Panel A. In particular WVRPss 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 10 displays the results of the estimation of equation 2.7 with the dependent variable being the firm level stock variance risk premium regressed individually on each of the four weather volatility uncertainty measures displayed in columns (1) to (4) respectively.[21]

[21] 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. Regression in Column (1)

INSERT TABLE 10 HERE

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. Table 10 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 original results of Panel A Table 10. 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 test the impact of the four 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 11 displays the results of the estimation of the predictive regression version 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

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.

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.[22] 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. $XDDss_{c,t-1}$).

INSERT TABLE 11 HERE

Table 11 Panel A finds that both the WRVOL and WRVOLss both positively predicts future credit spreads, hence a higher temperature futures volatility is associated with an expected future increasing credit spread for both monthly and seasonal contracts with coefficients (t-statistic) of $0.4e-3$ (6.41) and 0.01 (12.39) 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 $-4.0e-3$ (-6.94) and -0.01 (-18.13) respectively (both statistically significant at the 1% level). 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 11 Panel B (C) respectively re-estimates the monthly predictive panel regression version of equation 2.5 for the subsets of municipal bonds with time to maturity less (greater) than 15 years. In both Panels B and C both of WRVOL and WRVOLss, (WIVOLss, and WVRPss) positively (negatively) predicts future municipal bond credit spreads as in Panel A (all of the coefficients (with the exception of WRVOL in the subset of time to maturity greater than 15 years) statistically significant at the 1% level). Both of WRVOL and WRVOLss have

[22]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

comparable positive coefficients on the impact of municipal bond credit spreads with shorter term to maturity than longer term to maturity. Both of WIVOLss, and WVRPss have comparable negative coefficients on the impact of municipal bond credit spreads with longer term to maturity than shorter term to maturity.

3.2.2 Corporate Bond Main Results

Table 12 displays the results of the predictive regression version 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 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, and log-bond turnover, $XDD_{c,t-1}/XDDss_{c,t-1}$) are lagged by one month period.[23]

INSERT TABLE 12 HERE

Table 12 Panel A finds all of the WRVOL, WIVOLss, WRVOLss, and WVRPss negatively associated with future corporate credit spreads (only WIVOLss and WVRPss statistically significant at the 1% level), WIVOLss and WVRPss both negatively predicts future corporate credit spreads with coefficients (t-statistic) of -0.01 (-6.16) and -0.01 (-7.29) respectively (both statistically significant at the 1% level).

Table 12 Panel B and C re-estimates monthly predictive panel regression version of 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. The coefficient signs of WRVOL,

[23]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. 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.

WIVOLss, and WVRPss remain the same for both panels B and C as they were in panel A with statistical significance at the 1% level in Panel B and at the 1% level in Panel C (no statistical significance for WRVOLss is found in either panel B or C as in A). Both of WIVOLss, and WVRPss have comparable size negative coefficients on the impact of corporate credit spreads with shorter term to maturity than longer term to maturity.

3.2.3 Stock VRP Main Results

Table 13 displays the results of the estimation of equation 2.7 with the dependent variable being the firm level stock variance risk premium 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. Our results imply a higher cost of hedging temperature volatility leads to a expected future lower cost of hedging equity volatility uncertainty. Our results imply the benefits of hedging temperature volatility on the expected local financial economy.

INSERT TABLE 13 HERE

Table 13 panels B and C shows the results of monthly predictive panel regression version of 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 13.

3.3 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 14 HERE

Table 14 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 $\text{WVRPss}_{c,t}$ and $\text{WVRPss}_{c,t-1}$ for county c at times t and $t-1$ respectively. All municipal (corporate) 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.

In Panel A, we find that the coefficient of $\text{WVRPss}_{c,t}$ is positively associated with a higher municipal bond credit spread with coefficient (t-statistic) of 0.01 (14.79) while the coefficient of $\text{WVRPss}_{c,t-1}$ 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 $\text{WVRPss}_{c,t}$ is positively associated with a higher corporate bond credit spread with coefficient (t-statistic) of 0.01 (10.57) while the coefficient of WVRPss$_{c,t-1}$ 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 both Panels A and B 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 both columns and in both Panels, the coefficient of WVRPss$_{c,t}$ is positively associated with a higher credit spread and the coefficient of WVRPss$_{c,t-1}$ is negatively associated with a higher credit spread and comparing columns (3) and (4) finds that the impact of coefficients of WVRPss$_{c,t}$ and WVRPss$_{c,t-1}$ 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 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 15 (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 13.

INSERT TABLE 15 HERE

Table 16 Panels A (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. Adding state level measures of economic uncertainty does not change the predictive ability of the weather variance measures original results of Table 12.

INSERT TABLE 16 HERE

Table 16 Panel B 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 12.

Additional tests of equations 2.5 (and 2.6) controlling for the persistence of the municipal (corporate) credit spread (i.e. lag one period credit spread) do not change the sign of our results and are available upon request.

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.

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Table 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 2 Seasonal Strips Futures Options Summary Statistics

Atlanta HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	12956	0.16	0.16	0.08	3.35	0.08	0.11	0.19	0.21
Open Interest	12956	968	750	802	1	250	250	1250	2250
Time to Maturity (TTM)	12956	0.26	0.24	0.15	0.35	0.06	0.13	0.37	0.46
Chicago HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	8500	0.15	0.12	0.09	1.47	0.06	0.09	0.16	0.3
Open Interest	8500	958	500	976	2	50	250	1250	2250
Time to Maturity (TTM)	8500	0.23	0.21	0.14	0.35	0.06	0.12	0.34	0.43
Cincinnatti HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	3949	0.28	0.29	0.08	-0.2	0.16	0.24	0.33	0.37
Open Interest	3949	1149	1000	733	1	250	750	1500	2000
Time to Maturity (TTM)	3949	0.22	0.22	0.11	0.13	0.07	0.14	0.31	0.37
Dallas HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	11608	0.15	0.15	0.06	0.39	0.09	0.11	0.19	0.23
Open Interest	11608	899	750	694	1	250	300	1250	2000
Time to Maturity (TTM)	11608	0.23	0.23	0.13	0.21	0.06	0.13	0.34	0.42
Las Vegas HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	4800	0.1	0.07	0.06	2.66	0.04	0.06	0.11	0.18
Open Interest	4800	1490	1250	1278	1	250	500	2500	3000
Time to Maturity (TTM)	4800	0.2	0.19	0.13	0.52	0.04	0.1	0.29	0.37
Minneapolis HDD NOV Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	8291	0.16	0.13	0.1	1.39	0.07	0.1	0.19	0.33
Open Interest	8291	849	750	585	1	250	250	1250	1500
Time to Maturity (TTM)	8291	0.23	0.22	0.14	0.23	0.05	0.12	0.34	0.43
New York HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	20596	0.15	0.14	0.06	0.59	0.08	0.11	0.19	0.23
Open Interest	20596	1095	750	937	2	250	250	1500	2500
Time to Maturity (TTM)	20596	0.26	0.26	0.15	0.25	0.07	0.14	0.38	0.47
Sacramento HDD (CDD) NOV (MAY) Seasonal Strip Options									
State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Implied Volatility	2499	0.16	0.16	0.05	0.13	0.09	0.12	0.19	0.22
Open Interest	2499	1380	1000	962	1	250	500	2000	2250
Time to Maturity (TTM)	2499	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 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 Seasonal Strips Variance Measures Summary Statistics

State	N obs	Mean	Median	Std. Dev.	Skewness	10th Pctl.	25th Pctl.	75th Pctl.	90th Pctl.
Atlanta, GA									
WVRPss	68	0.0416	0.0405	0.0815	0.1834	−0.0811	−0.0099	0.0974	0.1402
WIVOLss	69	0.1611	0.1433	0.0841	2.6535	0.079	0.1194	0.1826	0.2427
RVOLss	70	0.1163	0.1096	0.0676	0.5479	0.0294	0.0742	0.151	0.2235
Chicago, IL									
WVRPss	59	0.0262	0.0269	0.0653	0.4349	−0.0568	−0.0235	0.0737	0.0996
WIVOLss	59	0.1511	0.12	0.0908	1.4863	0.0649	0.0926	0.1765	0.3406
RVOLss	59	0.1249	0.1029	0.0901	1.2561	0.0429	0.0562	0.1523	0.3025
Cincinnatti, OH									
WVRPss	36	0.0925	0.07	0.1231	−1.4752	0.0116	0.0367	0.1962	0.2614
WIVOLss	36	0.2861	0.3	0.0749	−0.1736	0.1879	0.2316	0.3398	0.3779
RVOLss	44	0.1753	0.1706	0.1098	3.1185	0.0653	0.1074	0.2242	0.2479
Dallas, TX									
WVRPss	63	0.0505	0.0413	0.0758	0.7341	−0.0123	0.0192	0.0761	0.1437
WIVOLss	65	0.1651	0.1511	0.0527	0.7628	0.1049	0.1227	0.1997	0.2431
RVOLss	63	0.1151	0.1014	0.0557	1.0433	0.06	0.0821	0.1402	0.1943
Las Vegas, NV									
WVRPss	32	0.025	0.0055	0.0671	1.8094	−0.0267	−0.0057	0.0392	0.0918
WIVOLss	33	0.111	0.0845	0.0664	1.6251	0.0547	0.0635	0.169	0.1853
RVOLss	32	0.0867	0.0787	0.0453	0.3418	0.0391	0.06	0.1104	0.1584
Minneapolis, MN									
WVRPss	56	0.0559	0.0528	0.0784	0.5868	−0.0314	0.0098	0.0968	0.1425
WIVOLss	59	0.1677	0.1383	0.0945	1.4251	0.0748	0.1075	0.1872	0.3373
RVOLss	57	0.1155	0.0815	0.0839	1.2747	0.046	0.0582	0.1261	0.2629
New York City, NY									
WVRPss	96	0.06	0.0522	0.0724	0.1521	−0.0196	0.0155	0.1013	0.1545
WIVOLss	96	0.1615	0.1515	0.0547	0.3614	0.0883	0.1188	0.1998	0.2296
RVOLss	101	0.0983	0.0879	0.0538	0.5593	0.0393	0.0686	0.1182	0.1813
Sacramento, CA									
WVRPss	27	0.0022	−0.0104	0.0633	0.9216	−0.0615	−0.0455	0.0425	0.1157
WIVOLss	27	0.1581	0.1581	0.0348	0.3535	0.109	0.1347	0.1864	0.1941
RVOLss	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 ($\text{WRVOLss}_{c,t}$), average option implied volatility ($\text{WIVOLss}_{c,t}$), and the weather variance risk premia ($\text{WVRPss}_{c,t}$, the difference between the $\text{WIVOLss}_{c,t}$ and $\text{WRVOLss}_{c,t}$) for each month t for each city c as outlined in Section 2.1.

Table 5 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 6 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 7 : 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 weather derivatives measures from Table 6. The sample period is monthly observations from January 2006 to December 2019.

Table 8 Municipal Bond Credit Spreads and WVRP (Contemporaneous)

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-1.4e-3$			
	(-25.66)			
$\text{WIVOLss}_{c,t}$		$-1e-3$		
		(-2.09)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-29.03)	
$\text{WVRPss}_{c,t}$				0.01
				(20.17)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-10.37)	(-3.08)	(2.02)	(0.62)
TTM_t	$-4.2e-3$	$-3.1e-3$	$-3.7e-3$	$-3.6e-3$
	(-16.44)	(-12.98)	(-15.65)	(-15.43)
$\log(\text{AmtOut/DollVolume})_t$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$
	(-13.02)	(-13.86)	(-13.96)	(-13.88)
R^2	81.07	81.17	81.47	81.32
N obs	59, 117	62, 748	62, 748	62, 748
Fixed Effects				
Bond CUSIP	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y

Panel B: $TTM < 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-1.6e-3$			
	(-29.42)			
$\text{WIVOLss}_{c,t}$		$1.2e-3$		
		(2.27)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-34.79)	
$\text{WVRPss}_{c,t}$				0.01
				(26.65)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-16.64)	(-8.79)	(-1.28)	(-3.6)
TTM_t	$-4.3e-3$	$-2.8e-3$	$-3.6e-3$	$-3.7e-3$
	(-16.21)	(-11.68)	(-15.18)	(-15.22)
$\log(\text{AmtOut/DollVolume})_t$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(-18.1)	(-18.81)	(-18.99)	(-18.81)
R^2	84.9	84.77	85.36	85.12
N obs	34, 451	37, 056	37, 056	37, 056
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y

Panel C: $TTM > 15$				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-1.1e-3$			
	(-11.5)			
$\text{WIVOLss}_{c,t}$		$-1.6e-3$		
		(-1.65)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-11.15)	
$\text{WVRPss}_{c,t}$				$4.1e-3$
				(7.37)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-2.16)	(1.54)	(2.86)	(2.63)
TTM_t	$-4e-3$	$-3.1e-3$	$-3.5e-3$	$-3.4e-3$
	(-8.64)	(-7.28)	(-8.16)	(-7.94)
$\log(\text{AmtOut/DollVolume})_t$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-1.9)	(-2.31)	(-2.37)	(-2.32)
R^2	80.71	80.73	80.84	80.78
N obs	24, 666	25, 692	25, 692	25, 692
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	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. $\text{WRVOL}_{c,t}$ ($\text{WRVOLss}_{c,t}$) 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 $\text{WRVOLss}_{c,t}$ 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. 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 9 Corporate Credit Spreads and WVRP (Contemporaneous)

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-1.1e-3$			
	(-4.32)			
$\text{WIVOLss}_{c,t}$		-0.01		
		(-4.16)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-7.3)	
$\text{WVRPss}_{c,t}$				0.01
				(5.43)
$XDD_i/XDDss_i$	$0e-3$	0.00	0.00	0.00
	(-4.82)	(-2.04)	(-1.94)	(-0.68)
TTM_t	$-0.6e-3$	$0.1e-3$	$0.7e-3$	$-0.2e-3$
	(-0.51)	(0.16)	(0.93)	(-0.28)
$Rating_t$	0.01	0.01	0.01	0.01
	(64.28)	(9.37)	(9.39)	(9.38)
$\log(\text{AmtOut/DollVolume})_t$	$0e-3$	0.00	$-0.1e-3$	0.00
	(-0.49)	(-0.23)	(-0.34)	(-0.26)
R^2	67.12	67.26	67.29	67.27
N obs	56.687	56,949	56,949	56,949
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)
$\text{WRVOL}_{c,t}$	$-1.3e-3$			
	(-4.1)			
$\text{WIVOLss}_{c,t}$		-0.01		
		(-3.99)		
$\text{WRVOLss}_{c,t}$			-0.02	
			(-7.7)	
$\text{WVRPss}_{c,t}$				0.01
				(3.9)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-4.89)	(-2.11)	(-2.09)	(-0.93)
TTM_t	$-0.1e-3$	$0.8e-3$	$1.4e-3$	$0.4e-3$
	(-0.06)	(0.55)	(0.94)	(0.25)
$Rating_t$	0.01	0.01	0.01	0.01
	(60.19)	(59.95)	(60.12)	(59.97)
$\log(\text{AmtOut/DollVolume})_t$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$	$-0.2e-3$
	(-2.16)	(-2.02)	(-2.2)	(-2.06)
R^2	67.73	67.83	67.86	67.83
N obs	44,929	45,089	45,089	45,089
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)
$\text{WRVOL}_{c,t}$	$-0.5e-3$			
	(-2.38)			
$\text{WIVOLss}_{c,t}$		$-3e-3$		
		(-1.86)		
$\text{WRVOLss}_{c,t}$			$-4.3e-3$	
			(-3.07)	
$\text{WVRPss}_{c,t}$				$1.5e-3$
				(1.27)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(0.62)	(1.67)	(1.89)	(2.33)
TTM_t	$-2.2e-3$	$-1.9e-3$	$-1.8e-3$	$-2.1e-3$
	(-2.11)	(-1.91)	(-1.74)	(-2.04)
$Rating_t$	$1.9e-3$	$1.9e-3$	$1.9e-3$	$1.9e-3$
	(17.71)	(17.43)	(17.45)	(17.39)
$\log(\text{AmtOut/DollVolume})_t$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-0.87)	(-0.94)	(-1.03)	(-0.92)
R^2	70.55	70.51	70.53	70.51
N obs	11,758	11,860	11,860	11,860
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. $\text{WRVOL}_{c,t}$ ($\text{WRVOLss}_{c,t}$) 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 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. $XDD_{c,t}/XDDss_{c,t}$ is the forecasted value of the end of month (seasonal strip) futures contract payoff for county c at time t. 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 10 Stock VRP and the WVRP (Contemporaneous)

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$4.6e-3$			
	(3.99)			
$\text{WIVOLss}_{c,t}$		0.01		
		(0.23)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-0.61)	
$\text{WVRPss}_{c,t}$				0.03
				(2.16)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(2.16)	(-0.34)	(-1.36)	(-0.24)
R^2	42.41	78.76	74.87	78.94
N obs	58,499	21,881	25,350	21,722
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)
$\text{WRVOL}_{c,t}$	0.01			
	(4.27)			
$\text{WIVOLss}_{c,t}$		0.01		
		(0.34)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-0.57)	
$\text{WVRPss}_{c,t}$				0.03
				(2.23)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(1.72)	(-0.71)	(-1.97)	(-0.81)
EPU_t	0.01	0.01	0.01	0.01
	(3.8)	(2.77)	(3.18)	(2.77)
R^2	42.43	78.77	78.76	74.87
N obs	58,499	21,881	25,350	21,722
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)
$\text{WRVOL}_{c,t}$	$4.6e-3$			
	(3.98)			
$\text{WIVOLss}_{c,t}$		0.01		
		(0.24)		
$\text{WRVOLss}_{c,t}$			-0.01	
			(-0.61)	
$\text{WVRPss}_{c,t}$				0.03
				(2.15)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(2.08)	(-0.32)	(-1.37)	(-0.22)
EJS SEPU_t	$1.5e-3$	$-0.8e-3$	$-0.4e-3$	$-0.9e-3$
	(0.85)	(-0.27)	(-0.14)	(-0.3)
R^2	42.41	78.76	74.88	78.94
N obs	58,499	21,881	25,350	21,722
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) 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 11 Municipal Bond Credit Spreads and WVRP (Predictive)

Panel A: Full Sample

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.4e-3$			
	(6.46)			
$\text{WIVOLss}_{c,t-1}$		$-4e-3$		
		(-6.94)		
$\text{WRVOLss}_{c,t-1}$			0.01	
			(12.39)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-18.13)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(15.26)	(10.64)	(8.66)	(4.98)
TTM_{t-1}	$-3.4e-3$	$-3.3e-3$	$0.2e-3$	$0.2e-3$
	(-13.15)	(-12.69)	(2.68)	(3.9)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-3.96)	(-3.93)	(-4.55)	(-4.31)
R^2	80.56	80.82	80.77	80.84
N obs	55,294	58,769	58,769	58,769
Fixed Effects				
Bond CUSIP	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y

Panel B: $TTM < 15$

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.9e-3$			
	(13.15)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-9.63)		
$\text{WRVOLss}_{c,t-1}$			0.01	
			(11.85)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-15.62)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(13.98)	(6.06)	(6.01)	(3.35)
TTM_{t-1}	$0.3e-3$	$0.3e-3$	$0.3e-3$	$0.3e-3$
	(4.54)	(4.91)	(4.43)	(5.44)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.1e-3$	$0e-3$	$0e-3$	$0e-3$
	(-2.98)	(-2.88)	(-3.03)	(-2.93)
R^2	84.66	84.71	84.74	84.79
N obs	32,358	34,837	34,837	34,837
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y

Panel C: $TTM > 15$

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$0.2e-3$			
	(1.59)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-5.44)		
$\text{WRVOLss}_{c,t-1}$			0.01	
			(6.86)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-9.31)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(7.13)	(4.13)	(5.51)	(3.6)
TTM_{t-1}	$0e-3$	$0e-3$	$0e-3$	$0.1e-3$
	(-0.21)	(0.18)	(0.01)	(0.65)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$	$-0.1e-3$
	(-2.84)	(-2.91)	(-2.91)	(-2.75)
R^2	79.66	79.84	79.86	79.9
N obs	22,936	23,932	23,932	23,932
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	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 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 $t-1$. 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.

Table 12 Corporate Credit Spreads and WVRP (Predictive)

Panel A: Full Sample

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-0.2e-3$			
	(-1.64)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-6.61)		
$\text{WRVOLss}_{c,t-1}$			$-0.2e-3$	
			(-0.16)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-7.29)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-1.76)	(-4.12)	(-2.03)	(-2.18)
TTM_{t-1}	$0.2e-3$	$0.7e-3$	$0.6e-3$	$0.7e-3$
	(0.68)	(1.61)	(1.37)	(1.66)
$Rating_{t-1}$	$3.7e-3$	0.01	0.01	0.01
	(8.75)	(8.59)	(8.58)	(8.58)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$0.2e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(2.32)	(-1.62)	(-1.61)	(-1.59)
R^2	76.21	67.52	67.5	67.51
N obs	165,747	56,013	56,013	56,013
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)
$\text{WRVOL}_{c,t-1}$	$-1.6e-3$			
	(-4.48)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-6.47)		
$\text{WRVOLss}_{c,t-1}$			$-1e-3$	
			(-0.52)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-6.98)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-3.22)	(-4.25)	(-2.32)	(-2.33)
TTM_{t-1}	$0.8e-3$	$1e-3$	$0.9e-3$	$1.1e-3$
	(1.18)	(1.63)	(1.38)	(1.68)
$Rating_{t-1}$	0.01	0.01	0.01	0.01
	(8.34)	(8.32)	(8.3)	(8.3)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.6e-3$	$-0.6e-3$	$-0.6e-3$	$-0.6e-3$
	(-2.55)	(-2.56)	(-2.55)	(-2.54)
R^2	68.49	68.66	68.63	68.65
N obs	44,130	44,284	44,284	44,284
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)
$\text{WRVOL}_{c,t-1}$	$-0.5e-3$			
	(-2.31)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-2.73)		
$\text{WRVOLss}_{c,t-1}$			$2.1e-3$	
			(1.37)	
$\text{WVRPss}_{c,t-1}$				-0.01
				(-3.99)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(0.2)	(0.35)	(1.82)	(1.24)
TTM_{t-1}	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(-1.01)	(-0.83)	(-0.96)	(-0.81)
$Rating_{t-1}$	$1.6e-3$	$1.5e-3$	$1.5e-3$	$1.5e-3$
	(3.54)	(3.46)	(3.45)	(3.45)
$\log(\text{AmtOut/DollVolume})_{t-1}$	0.00	0.00	0.00	0.00
	(-0.18)	(-0.25)	(-0.21)	(-0.21)
R^2	70.53	70.53	70.51	70.55
N obs	11,624	11,729	11,729	11,729
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 $t-1$. $\text{WRVOL}_{c,t-1}$ ($\text{WRVOLss}_{c,t-1}$) 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 $t-1$. 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 13 Stock VRP and the WVRP (Predictive)

Panel A: Full Sample				
Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t}$	$-2.3e-3$			
	(-2.47)			
$\text{WIVOLss}_{c,t}$		-0.02		
		(-1.16)		
$\text{WRVOLss}_{c,t}$			0.04	
			(4.08)	
$\text{WVRPss}_{c,t}$				-0.05
				(-5.07)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.94)	(-1.62)	(-0.57)	(-1.82)
$StockVRP_t$	0.67	0.67	0.68	0.67
	(33.21)	(26.5)	(28.62)	(26.6)
R^2	68.72	87.44	85.01	87.52
N obs	57,784	21,586	25,030	21,429
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)		
$\text{WRVOLss}_{c,t}$			0.04	
			(4.07)	
$\text{WVRPss}_{c,t}$				-0.05
				(-4.89)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-3.14)	(-2.13)	(-1.51)	(-2.46)
$StockVRP_t$	0.67	0.67	0.68	0.67
	(33.18)	(26.45)	(28.57)	(26.55)
EPU_t	$2.8e-3$	0.01	0.01	0.01
	(2.06)	(3.18)	(4.43)	(2.85)
R^2	68.73	87.45	85.02	87.53
N obs	57,784	21,586	25,030	21,429
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		
		(-1.13)		
$\text{WRVOLss}_{c,t}$			0.04	
			(4.05)	
$\text{WVRPss}_{c,t}$				-0.05
				(-4.91)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(-2.85)	(-1.39)	(-0.46)	(-1.62)
$StockVRP_t$	0.67	0.67	0.68	0.67
	(33.21)	(26.49)	(28.62)	(26.59)
EJS SEPU_t	$-1.5e-3$	-0.01	$-3.7e-3$	-0.01
	(-1.33)	(-2.89)	(-1.92)	(-2.63)
R^2	68.72	87.45	85.01	87.53
N obs	57,784	21,586	25,030	21,429
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 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 $\text{WRVOLss}_{c,t}$. $XDD_{c,t}/XDDss_{c,t}$ 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 14 Resolution of Uncertainty of Municipal and Corporate Credit Spreads

Panel A: Municipal Credit Spreads				
Variable	(1)	(2)	(3)	(4)
$\text{WVRPss}_{c,t}$	0.01	0.01	0.01	$4.2e-3$
	(14.79)	(18.03)	(23.54)	(6.83)
$\text{WVRPss}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-21.01)	(-24.65)	(-23.59)	(-11.53)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	$(0e-3)$	(-0.89)	(-4.3)	(1.2)
TTM_{t-1}	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.3e-3$
	(3.55)	(3.59)	(3.62)	(2.09)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.1e-3$	$0e-3$	$0e-3$	$0e-3$
	(-4.46)	(-0.55)	(0.57)	(-1.4)
CS_{t-1}		0.24	0.19	0.21
		(55.64)	(32.2)	(30.68)
R^2	81.37	82.58	85.69	81.57
N obs	52,642	52,642	31,010	21,632
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y
S.E. Clustering: Bond	Y	Y	Y	Y

Panel B: Corporate Credit Spreads				
Variable	(1)	(2)	(3)	(4)
$\text{WVRPss}_{c,t}$	0.01	0.01	0.01	$4.2e-3$
	(10.57)	(14.28)	(21.42)	(5.37)
$\text{WVRPss}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-16.79)	(-19.71)	(-18.15)	(-9.39)
$XDD_i/XDDss_i$	0.00	0.00	0.00	0.00
	(0.00)	(-0.84)	(-4.48)	(1.14)
TTM_{t-1}	$0.2e-3$	$0.2e-3$	$0.2e-3$	$0.3e-3$
	(2.32)	(2.21)	(2.18)	(1.22)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.1e-3$	0.00	0.00	0.00
	(-2.97)	(-0.39)	(0.47)	(-0.93)
CS_{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
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 in Panel A (B) being the municipal (corporate) bond credit spreads (at time t) regressed on both $\text{WVRPss}_{c,t}$ and $\text{WVRPss}_{c,t-1}$ 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 15 Robustness: Stock VRP and the WVRP (Predictive)

Panel A: Full Sample and controls

Variable	(1)	(2)	(3)	(4)
$\text{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-1.59)		
$\text{WRVOLss}_{c,t-1}$			0.05	
			(2.83)	
$\text{WVRPss}_{c,t-1}$				-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)
$\text{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-1.6)		
$\text{WRVOLss}_{c,t-1}$			0.05	
			(2.83)	
$\text{WVRPss}_{c,t-1}$				-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)
$\text{WRVOL}_{c,t-1}$	$-2e-3$			
	(-2.16)			
$\text{WIVOLss}_{c,t-1}$		-0.01		
		(-1.6)		
$\text{WRVOLss}_{c,t-1}$			0.05	
			(2.84)	
$\text{WVRPss}_{c,t-1}$				-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. $\text{WRVOL}_{c,t}$ ($\text{WRVOLss}_{c,t}$) 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 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. $XDD_{c,t}/XDDss_{c,t}$ 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 16 Robustness: Corporate Credit Spreads and WVRP (Predictive)

Panel A: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\text{WVRPss}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-5.16)	(-5.18)	(-5.24)	(-5.17)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-2.61)	(-3.15)	(-3.18)	(-3.14)
TTM_{t-1}	$0.7e-3$	$1.1e-3$	$1.1e-3$	$1.1e-3$
	$(1.1e-3)$	(2.48)	(2.48)	(2.45)
$Rating_{t-1}$	0.01	0.01	0.01	0.01
	(51.9)	(51.96)	(51.91)	(51.99)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.2e-3$
	(-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)	(2.4)	(2.35)
cc risk ew_{t-1}		-1.1		
		(-1.95)		
cc expo ew_{t-1}			0.14	
			(1.69)	
op risk ew_{t-1}				-3.34
				(-2.21)
R^2	64.85	65.2	65.2	65.2
N obs	56,013	52,999	52,999	52,999
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	Y	Y	Y	Y

Panel B: Full Sample and controls				
Variable	(1)	(2)	(3)	(4)
$\text{WVRPss}_{c,t-1}$	-0.01	-0.01	-0.01	-0.01
	(-4.85)	(-4.76)	(-4.84)	(-4.76)
$XDD_i/XDDss_i$	$0e-3$	$0e-3$	$0e-3$	$0e-3$
	(-1.79)	(-2.48)	(-2.51)	(-2.46)
TTM_{t-1}	$0.7e-3$	$1.1e-3$	$1.1e-3$	$1.1e-3$
	$(1.1e-3)$	(2.58)	(2.58)	(2.56)
$Rating_{t-1}$	0.01	0.01	0.01	0.01
	(51.76)	(51.85)	(51.8)	(51.88)
$\log(\text{AmtOut/DollVolume})_{t-1}$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$	$-0.3e-3$
	(-3.31)	(-2.88)	(-2.87)	(-2.86)
EJS SEPU_{t-1}	$-0.5e-3$	$-0.7e-3$	$-0.7e-3$	$-0.7e-3$
	(-1.68)	(-2.56)	(-2.41)	(-2.56)
cc risk ew_{t-1}		-1.17		
		(-2.08)		
cc expo ew_{t-1}			0.13	
			(1.52)	
op risk ew_{t-1}				-3.49
				(-2.32)
R^2	64.84	65.2	65.2	65.2
N obs	56,013	52,999	52,999	52,999
Fixed Effects				
Bond	Y	Y	Y	Y
Year x Quarter	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 $t-1$. $\text{WVRPss}_{c,t-1}$ 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 $t-1$. 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.