A Market-based Measure of Climate Risk for Cities

Alexander W. Butler and Cihan Uzmanoglu*

July 9, 2024

Abstract

We use information from financial markets to construct a comprehensive measure of cities' economic exposure to climate-related risks. Studying a large sample of municipal bonds issued by U.S. cities, we document substantial variation in how municipal bond prices respond to innovations in climate news. We find that this variation can provide a useful and holistic measure of cities' economic exposure to a wide array of manifestations of climate risk, and influence cities' cost of borrowing. We then show how our measure of climate risk exposure relates to city characteristics, such as geography, poverty, and local attitudes toward climate change science.

Keywords: Climate Change; Global Warming; Climate Risk; Physical Risk; Transition Risk; Climate News; Municipal Bonds; Cost of Capital; Yield Spread; Poverty

JEL Codes: G24; G12; G18; Q54; Q52; Q58

* Alexander W. Butler, Rice University, alex.butler@rice.edu; Cihan Uzmanoglu, Binghamton University, cuzmanog@binghamton.edu. We thank Lee Ann Butler, and the seminar participants at North Carolina State University, Utrecht University, University of Georgia, and University of Texas Rio Grande Valley for comments, and Johannes Stroebel for making the climate news indexes used in this paper available at his web-site.

1. Introduction

We use the financial instruments issued by municipalities in the United States (U.S.) to estimate these municipalities' economic exposure to climate change. Beyond the direct costs climate change imposes on people (e.g., Nordhaus (1977, 2019); Stern (2008); Lesk et al. (2016); Litterman et al. (2020)), climate change poses a significant economic risk for the municipalities in which people live, as climate events may disrupt local economic activities and reduce tax bases. Indeed, the literature shows that municipalities with greater exposures to sea level rise and heat stress have higher borrowing costs (Painter (2020); Acharya et al. (2023)), that prices of properties exposed to sea level rise decline (Bernstein et al. (2019)), and that mortgages on those exposed properties face higher interest rates (Nguyen et al. (2022)).

However, geographic exposure to climate change is not the only risk that municipalities face. Most research exploring the link between climate risk and asset prices examines the physical risk of climate change, but other climate-related channels may also impact asset prices. One such channel is the *transition risk* associated with climate change, which includes the risk arising from transitioning to a sustainable economy and the associated climate policy uncertainties (e.g., Giglio et al. (2021); Bolton and Kacperczyk (2023)).

If both physical and transition risks from climate change are important, a measure of climate exposure that captures both sources of economic risk would be a more comprehensive lens into issuers' climate-related exposure than physical-only measures. Systematically measuring municipalities' exposures to climate risks is challenging because of offsetting or exacerbating economic factors. A city located near the coast, such as Los Angeles CA, may be resilient to climate change if it has a diverse economy and is home to companies that would not be adversely impacted by net-zero carbon emissions policies (Sautner et al. (2023)). On the other hand, a nearby inland city, such as Bakersville CA, may have high economic exposure to climate change if its local economy is fragile and relies on the production of fossil fuels that can be left stranded as carbon taxes increase (Raimi (2021)).

In this paper, we take a new approach to measuring cities' economic exposure to climate-related risks, which we infer from the municipal bond market. Bond prices reflect investors' expectations about the issuer's ability to make payments as promised and recovery in the event of a default. We hypothesize that municipal bonds' prices reflect perceived risks from climate change, both physical and transition. Those risks are likely to become more salient as important news about climate change is reported. Our approach directly estimates the sensitivity of individual cities' municipal bond prices to the arrival of climate news. We hypothesize that municipal bonds whose prices decline more in response to the arrival of negative climate news (henceforth, climate news generally refers to negative climate news) have greater financial exposures to climate change. Assuming markets are efficient, this sensitivity of a municipal bond's prices to climate news—*climate news sensitivity*—would reflect the bond's, and its issuer's, exposure to climate risks.

To estimate climate news sensitivities, we rely on the climate news indexes developed by Engle et al. (2020). These indexes cover climate change-related news, such as extreme weather events, temperature trends, and sea level changes. These indexes are national; our innovation is to project a local measure of economic health onto the indexes to produce a measure of a locale's exposure to climate risk. We compute climate news sensitivities for municipal bonds from 240 U.S. cities by regressing monthly municipal bond excess returns on innovations in monthly climate news indexes and numerous controls. This procedure allows us to create estimates of securities' and, in turn, issuers' exposure to climate change. We invert the signs of climate news sensitivities so that a higher climate news sensitivity indicates greater economic exposure to climate change.

We find that climate news sensitivities vary intuitively with the physical climate risk characteristics of cities. For instance, cities that are predicted to experience higher climate-related damages and those that have historically experienced more flood and coastal flood incidences exhibit higher climate news sensitivities. On the other hand, our approach to estimating city-level climate exposure reveals some interesting surprises, such as the fact that Seattle WA and Tacoma WA, two cities sharing the coastline of Puget Sound fewer than 40 miles apart, have very different climate sensitivities. Why? Because of the different economic and financial health of the two cities. Tacoma has a much lower household income, a higher poverty rate, and weaker financial stability than Seattle, resulting in twice the economic vulnerability to climate change (Hsiang et al. (2017)). Moreover, municipal bonds issued in states with greater carbon emission intensities have higher climate news sensitivities, suggesting that climate news sensitivities reflect the transition risk in addition to the physical risk associated with climate change (see also Stroebel and Wurgler (2021)).

Our measure of climate risk exposure has desirable properties: granular variation both geographically and through time. In principle, we can estimate climate news sensitivity for any city with publicly traded municipal bonds. The measure also has good time series properties because we can compute how a city's climate news sensitivity changes as both climate news coverage changes and as municipal bond prices change. We verify that our measure contains information incremental to the physical aspects of climate risk by confirming that our results are unchanged if we let our measure and measures of physical risks like sea level rise compete for explanatory power. By reflecting all types of physical and economic risks from climate change relevant to an issuer, climate news sensitivity is agnostic as to what type of risk is important. Consider Houston TX: is flood risk more or less important than heat exposure, and is either more or less important than the city's economic dependence on energy? Our climate sensitivity measure reflects all of these in the proportions that the financial markets deem relevant.

We then examine the relationship between climate news sensitivities and municipal bonds' monthly yield spreads. Overall, we find that climate news sensitivities are positively associated with yield spreads: municipal bonds with higher climate risk exposures have higher costs of borrowing. We also find a similar relationship when studying the offering yield spreads on new bond issues. Our estimates indicate that a one-standard deviation increase in a city's climate news sensitivity is associated with a 1.74% to 11.19% increase in the average yield spreads of its municipal bonds, comparable to the change in yield spreads resulting from a one-notch drop in credit ratings.

Next, we validate our approach by examining whether our findings are consistent with other studies of climate risk. We find that the relationship between yield spreads and climate news sensitivities is more pronounced during the post-2013 period, relative to the pre-2013 period, after which physical climate risks began to be priced in the municipal bond market (as in Goldsmith-Pinkham et al. (2023)). Our estimates are stronger when media coverage of climate change-related news increases, consistent with attention to climate change influencing asset prices (e.g., Choi et al. (2020)). These findings provide evidence that the time-series variation in our estimates are correlated with climate change-related trends in the markets.

Our estimates vary intuitively with the characteristics of municipal bonds. In particular, we find that the positive relationship between climate news sensitivity and yield spread is more pronounced among longer term bonds and riskier bonds. As climate risk is a long-run risk that would matter more to municipal bonds with marginal credit quality, these findings provide additional evidence supporting the climate risk mechanism driving our findings and suggest that climate risk exposure reflects a default risk for these bonds.

We then turn our attention to how cities' demographics, such as poverty levels, reflect in municipal bonds' climate news sensitivities. The economic development literature is rich in studies of how climate change and poverty interact. Climate change can create poverty traps (Hallegatte et al. (2014)), in part because the impacts of climate change are regressive and poor people are overexposed and more vulnerable to climate change (e.g., Park et al. (2018), Winsemius et al. (2018), and Skoufias et al. (2011)). Climate change also disproportionately affects the health outcomes of poor people (Carleton et al. (2022)), and health outcomes can have significant impacts on municipal financing (Cornaggia et al. (2022)). Our results extend the climate-poverty literature: we find that cities with higher poverty rates have higher climate news sensitivities, consistent with these cities having greater economic exposure to climate change. These results are important to understand better the disparate human toll that climate risk takes. Moreover, local beliefs about climate change influence climate news sensitivities. In cities where a higher percentage of adults believe that global warming is harmful and a greater fraction of citizens vote for Democrats in presidential elections, the climate news sensitivities are higher, indicating a greater economic exposure to climate news.

Our findings contribute to the growing literature that examines the impact of climate change on financial markets by constructing a market-based measure that captures the economic exposure of cities to both physical and transition risks.[1] Our findings also bear significant policy implications, as this novel measure helps identify cities that are financially vulnerable to climate

[1] See Giglio, Kelly, and Stroebel (2021) for an excellent review of the climate finance literature.

change. For instance, we document that poorer cities, which already grapple with funding their educational and infrastructure needs, could encounter greater financial difficulties as climate risks materialize and lead to disproportionally higher borrowing costs for them.

2. Data, Sample Selection, and Descriptive Statistics

We obtain transaction-level data on municipal bonds from the Municipal Securities Rulemaking Board (MSRB). This dataset is available to us through the Wharton Research Database Services (WRDS) between January 2005 and June 2022. Similar to Green, Li, and Schurhoff (2010), we perform several quality control checks to eliminate potential pricing errors. Appendix A provides the details of these data steps. We obtain the characteristics of these municipal bonds (e.g., offering amounts, tax treatments, credit ratings from S&P, Fitch, and Moody's as of trade dates) from Bloomberg using their CUSIP identifiers, and retain fixed coupon general obligation bonds issued by cities. We identify the bonds issued by cities based on the issuer classification of Bloomberg.[2]

To compute daily yields, we use daily transaction-level bond prices weighted by trade amounts. Our dependent variable—*Yield Spread*—is the difference between these daily municipal bond yields and maturity-matched Treasury yields. We obtain Treasury yields from the Treasury's website, and linearly interpolate them to align with the maturities of municipal bonds.[3] In Section 4, we show that our findings are robust to using alternative benchmarks to compute yield spreads.

[2] Bloomberg's city classification includes cities, towns, and villages. We manually check issuer names and eliminate bonds issued by entities other than cities, towns, or villages.

[3] https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics

We then generate our monthly municipal bond dataset by keeping the last observation in each month for each bond. This approach creates a more balanced sample compared to the daily sample, as each bond in the monthly dataset is represented only once in a month. In Section 4, we also report the results from using the latest trades executed during the last 10 days of a month.

To estimate *Climate News Sensitivity*, we use the Wall Street Journal (WSJ)-based climate change news innovation index of Engle et al. (2020). Innovations in this index capture the changes in climate news coverage in the WSJ. This news index may include both positive and negative news about climate change, but as Engle et al. (2020) show, most of the news is negative. In Section 4, we show that our findings are robust to using a news index that specifically captures negative climate news.

The WSJ-based innovation index is computed in monthly frequency between January 1984 and June 2017, and available for download at Johannes Stroebel's website.[4] For each bond and in each month, we run a regression of monthly municipal bond returns using the previous 60-month period, and require at least 30 monthly returns to estimate *Climate News Sensitivity*. Our regression equation to estimate *Climate News Sensitivity* is as follows:

$$R_{i,t}=\alpha+\beta Climate\ News\ Innovation_t+X_t^{'}\gamma+\varepsilon_{i,t}\ , \tag{1}$$

where $R_{i,t}$ is the monthly return ($Ret_{i,t}$) of bond i in month t minus the return on one-month Treasury bill (RF_t) obtained from Kenneth French's website,[5] and $Climate\ News\ Innovation_t$ is the WSJ based climate innovation index of Engle et al. (2020).

In this regression equation, X_t represents a vector of additional controls to alleviate the concern that *Climate News Sensitivity* (β) may capture a risk premium rather than the sensitivities

[4] https://pages.stern.nyu.edu/~jstroebe/Data/EGLKS_data.xlsx

[5] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

of bond prices to climate news. We control for the excess stock market return (MKT_t) from Kenneth French's website to account for market news. In Section 4, we report the results controlling for aggregate municipal bond market returns as an alternative proxy for market news. We also control for the term spread ($TERM_t$) and credit spread ($CREDIT_t$) in this regression, as Fama and French (1993) argue that these common factors along with excess stock market returns explain returns on stocks and bonds. Similar to Fama and French (1993), we define $TERM_t$ as the difference between monthly returns of a 10-year Treasury bond computed using the S&P's U.S. Treasury Bond 10-Year Total Return Index and a one-month Treasury bill, and $CREDIT_t$ as the difference in monthly returns of Bloomberg's BBB-rated and AAA-rated U.S. Municipal Bond Total Return Indexes.

We compute monthly bond returns using the weighted average transaction prices as of the last trade date in a month, where the weights are based on trade amounts. For bond i in month t, we compute returns ($Ret_{i,t}$) as follows:

$$Ret_{i,t}=\frac{Price_{i,t}+Accrued\ Interest_{i,t}+Coupon\ Payment_{i,t}}{Price_{i,t-1}+Accrued\ Interest_{i,t-1}}-1\ , \tag{2}$$

where $Price_{i,t}$ ($Price_{i,t-1}$) is the weighted average price on the last traded day of month t (t-1), and $Coupon\ Payment_{i,t}$ is the coupons received in month t. We calculate *Accrued Interest* using a 30/360 day-count convention.

After these steps, our sample includes 49,681 bond-month observations with available *Yield Spread* and *Climate News Sensitivity*, contributed by 240 U.S. cities. We drop small cities with populations fewer than 50,000, which is about the 25th percentile of population size in our sample, and keep only those cities that contribute multiple bonds to the sample. These additional steps help alleviate the influence that numerous small cities, which contribute few observations to the sample, may have on our estimates. In Section 4, we demonstrate that these sample selection choices do not materially influence our baseline estimates.

Our final sample includes 45,056 bond-month observations. This sample comes from 1,699 unique municipal bonds issued by 104 U.S. cities in 30 states. New York City contributes the largest number of transactions to our sample (50.14%), followed by Chicago (12.95%), Houston (3.34%), Philadelphia (2.29%), and Phoenix (2.29%). Table 1 reports the descriptive statistics for the variables used in our regressions, and Appendix B provides the detailed definitions of these variables. To reduce the influence of outliers, we winsorize all of the continuous variables at the 1st and 99th percentiles in each year, unless indicated otherwise (see Appendix B for detailed variable definitions). In Section 4, we demonstrate that our results are robust to not winsorizing the variables.

The average *Yield Spread* is 1.43%, indicating that yields on municipal bonds are on average 1.43 percentage points higher than those on maturity-matched Treasury bonds. These statistics are within the range of municipal bond yields and yield spreads reported in the literature (e.g., Ang, Bhansali, and Xing (2014); Schwert (2017); Gao, Lee, and Murphy (2020)). A positive yield spread suggests that, on average, default and (il)liquidity premiums of municipal bonds outweigh their tax advantages over Treasury bonds during our analysis period.

Consistent with differences in credit and liquidity characteristics of municipal and Treasury bonds driving the positive *Yield Spread*, we find that the majority of municipal bonds in our sample have ratings below AAA and trade infrequently. Table 1 shows that, based on the median of their ratings from Moody's, S&P, and Fitch as of their trade dates, the credit ratings of the observations in our sample with their percent representation in parenthesis are as follows: AAA (7.64%), AA (72.85%), A (13.69%), BBB (4.59%), and below BBB (0.67%). The remaining 0.56% of the observations are unrated by Moody's, S&P, or Fitch as of their trade dates. Municipal bonds are illiquid, with the average (median) bond in our sample being traded 10.52 (7) times in the month prior to the observation date.

The average offering amount of municipal bonds is $33.8 million and 12.28% of these bonds are issued through a competitive sale as opposed to a negotiated sale. On their trade dates, the average bond maturity in our sample is 10.13 years with a standard deviation of 6.63 years. The majority of bonds in our sample are callable (70.94%), and some of them have sinking fund provisions (24.4%) and credit enhancements (33.6%).[6] As expected, most of the observations in our sample are exempt from state (85.56%) and Federal (90.86%) taxes.

Our beta estimates on excess stock market returns, term spread, and credit spread are within the range of Fama and French's estimates. Fama and French (1993) show that the stock market beta is close to zero for both Treasury bonds and investment grade corporate bonds. Consistent with this finding, we find that the average *Stock Market Beta* is zero for the municipal bonds in our sample. In addition, Fama and French (1993) show that beta estimates on term spread and credit spread are close to one for investment grade corporate bonds, and they are between zero and one for Treasury bonds. We find that the averages of *Term Spread Beta* and *Credit Spread Beta* in our sample are 0.26 and 0.54, respectively, suggesting that municipal bonds behave more like Treasury bonds than investment grade corporate bonds.

Controlling for excess stock market return, term spread, and credit spread factors, we find that the average *Climate News Sensitivity* in our sample is 0.22. For ease of interpretation, we invert the signs of these estimates, so that higher *Climate News Sensitivity* is associated with higher climate risk exposure. After this transformation, the average *Climate News Sensitivity* in our

[6] We observe in Table 1 that there are more credit enhanced bonds than AAA-rated bonds in our sample. As the rating of a credit enhanced bond takes the higher of the issuer's and insurer's ratings, this observation suggests that not all insurers have AAA ratings. We check credit ratings information from Bloomberg and confirm that this is the case.

sample is −0.22 and has a standard deviation of 1.78. The 10th and 90th percentile values of *Climate News Sensitivity* are −2.34 and 1.93, respectively. This heterogeneity in *Climate News Sensitivity* suggests that bonds have substantially different sensitivities to innovations in climate news. A simple univariate regression of yield spreads on *Climate News Sensitivity* produces an average yield spread estimate of 1.43% with 10th and 90th percentile values of *Climate News Sensitivity* corresponding to yield spread estimates of 1.35% and 1.51%, respectively.

In order to identify which cities (and with what characteristics) are most exposed to climate risk, we aggregate the bond-level *Climate News Sensitivities* at the city level. Appendix C reports the average *Climate News Sensitivity* at the city level and the city-level *Climate News Sensitivities* orthogonalized to bond characteristics, and Appendix D presents these city-level *Climate News Sensitivities* on a map. We observe that *Climate News Sensitivities* vary among cities even within short distances.

Finally, we collect the characteristics of cities in our sample from their latest annual financial reports prior to the trade dates from Bloomberg. The average city in our sample has $13.9 billion assets, a net income to assets ratio of 1.46%, a cash to assets ratio of 24.07%, and a liabilities to assets ratio of 62.54%. Overall, consistent with the majority of observations in our sample having investment grade ratings, these cities appear to be profitable and have low leverage.

3. Empirical Design and Findings

In this section, we investigate the relationship between *Yield Spread* and *Climate News Sensitivity*, examine how this relationship varies through time and in cross-section, study the characteristics of *Climate News Sensitivity*, explore the mechanism driving the pricing of climate risks into yield spreads, revisit our baseline findings among new bond issuances, and discuss the policy implications of our findings.

3.1. The Cross-Sectional Relationship between Yield Spread and Climate News Sensitivity

We run Fama and MacBeth (1973) regressions to study the cross-sectional relationship between yield spreads of municipal bonds and their climate news sensitivities. More specifically, we first run the following regression in each month (*t*) during our analysis period between January 2010 and July 2017 (91 monthly regressions):

$$Yield\ Spread_i = \alpha + \beta Climate\ News\ Sensitivity_i + X_i'\gamma + \varepsilon_i\ , \qquad (3)$$

where X_i is a vector of control variables that include *Bond Characteristics*, *Beta Estimates*, and *City Financials*, and ε_i is the error term.

Bond Characteristics are *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* are *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* are *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. Section 2 and Appendix B provide the definitions and data sources of these variables.

Then, we report the averages of these coefficient estimates and their statistical significances computed using Newey-West (Newey and West (1987)) adjusted standard errors with 3-month lags. We show in Section 4 that our findings are similar when using alternative number of lags to adjust standard errors. Table 2 reports the coefficient estimate on *Climate News Sensitivity*, which is the independent variable of interest. We multiply the coefficient estimates on *Climate News Sensitivity* by 100 in all the tables to facilitate interpreting their economic magnitudes.

In Table 2, Column (1) reports the results from a parsimonious model without any controls, and shows that the coefficient estimate on *Climate News Sensitivity* is 2.33, which is statistically significant at the 1% level. This finding indicates a strong positive relationship between *Climate News Sensitivity* and *Yield Spread*. Columns (2) through (4) in Table 2 add *Bond Characteristics*, *Beta Estimates*, and *City Financials* as additional controls, respectively. We find in untabulated results that the coefficient estimates on the controls are largely consistent with their economic interpretations. For instance, larger bond issues, competitive bond offerings, and bonds that are exempt from taxes have significantly lower yield spreads, and bonds rated below investment grade and bonds issued by cities with higher leverage have higher yield spreads.

Controlling for the determinants of *Yield Spread* in Columns (2)−(4) of Table 2, we find that the coefficient estimates on *Climate News Sensitivity* are between 1.40 and 1.90, which are statistically significant at the 1% level. As we discuss in Section 4, the magnitude of this estimate can be as large as 8.99 in alternative empirical specifications. Accordingly, a one-standard deviation (1.78) increase in *Climate News Sensitivity* is associated with an increase of 1.74% (1.74 = 1.40×1.78/1.43) to 11.19% (11.19 = 8.99×1.78/1.43) in average yield spreads. The economic magnitude of these estimates is as large as a one-notch drop in credit ratings has on yield spreads.[7]

As the 10^{th} and 90^{th} percentile values of *Climate News Sensitivity* are −2.34 and 1.93, respectively, the difference in borrowing costs of high versus low *Climate News Sensitivity* bonds

[7] We find in untabulated results that the coefficient estimate on median numerical ratings—the median of numerical ratings (e.g., AAA = 22, AA+ = 21, AA = 20) from S&P, Moody's, and Fitch—is −0.14 in our baseline regression of yield spreads. This suggests that a one-notch drop in credit ratings is associated with a 9.79% (0.0979 = −1×−0.14/1.43) increase in yield spreads.

in our sample can be economically large. A difference of 4.27 (4.27 = 1.93 – (–2.34)) in *Climate News Sensitivity* would be associated with a 4.18% (4.18 = 1.40×4.27/1.43) to 26.84% (26.84 = 8.99×4.27/1.43) difference in average yield spreads. In practical terms, our baseline estimates suggest that an average size ($33.8 million) bond issued by a 90th percentile climate risk city pays an additional $20 thousand (0.02 = 1.40×4.27×33.8/10,000) to $130 thousand (0.13 = 8.99×4.27×33.8/10,000) per year in excess interest compared to what a city at the 10th percentile of climate risk city pays. This extra interest expense of $130 thousand per bond each year is enough to cover a city's welfare spending for at least 50 recipients.[8]

In the next section, we implement alternative regression approaches to study the relationship between *Yield Spread* and *Climate News Sensitivity*.

3.2. Fixed Effects Regressions of Yield Spreads

In this section, we run ordinary least squares (OLS) regressions with issuer (i.e., city) fixed effects to examine the influence of within-city variation in *Climate News Sensitivity* on *Yield Spread*. If *Climate News Sensitivity* proxies for climate risk exposures of cities, we would expect the coefficient estimate on *Climate News Sensitivity* to decline with issuer-fixed effects, as the climate risk characteristics of cities are expected to be somewhat time invariant. On the other hand, as climate risk-related issues have received greater attention in recent years, the influence of *Climate News Sensitivity* on *Yield Spread* may also vary through time.

Our regression model is as follows:

$$Yield\ Spread_{i,t} = \alpha + \alpha_j + \alpha_{Trade\ Year\text{-}Month} + \beta Climate\ News\ Sensitivity_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t}\ , \qquad (4)$$

[8] According the Urban Institute's website (https://www.urban.org/policy-centers/cross-center-initiatives/state-and-local-finance-initiative/state-and-local-backgrounders/state-and-local-expenditures), on average, state and local governments spent $2,387 per capita on public welfare in 2020.

where α_j and $\alpha_{Trade\ Year\text{-}Month}$ indicate issuer and trade year-month fixed effects, and the rest of the variables are the same as those in Column (4) of Table 2. In brief, in addition to issuer and trade year-month fixed effects, this regression controls for *Bond Characteristics*, *Beta Estimates*, and *City Financials*. We cluster the standard errors at the issuer level.

Columns (1) through (4) of Table 3 report the regression results with the number of control variables increasing incrementally in each column, as in Table 2. Consistent with our estimates from Fama-MacBeth regressions, the coefficient estimates on *Climate News Sensitivity* are positive and statistically significant. However, the magnitudes of these coefficient estimates are lower than those in our baseline specification. With the full set of controls in Column (4), the coefficient estimate declines from 1.40 to 1.08 with issuer fixed effects. This suggests that our baseline regression results are explained by both time-invariant and time-varying associations between climate risk characteristics of cities and the yield spreads on their bonds.

In the next section, we explore the variation in our baseline estimates across alternative periods to understand the mechanisms driving the relationship between *Climate News Sensitivity* and *Yield Spread*.

3.3. Time-Series Variation in the Relation between Yield Spread and Climate News Sensitivity

In this section, we investigate the variation in the relationship between *Yield Spread* and *Climate News Sensitivity* across subsample periods. We begin by running our baseline regression (Column (4), Table 2) separately during the pre- and post-2013 periods. We split our sample by 2013, as Goldsmith-Pinkham et al. (2023) demonstrate that the physical climate risk began to be priced in municipal bond yields from that year onwards.

Column (1) of Table 4 reports the results of our baseline regression estimated before January 2013, and Column (2) of the same table reports the results estimated after (including)

January 2013. We find that the coefficient estimate on *Climate News Sensitivity* is 0.91, but statistically insignificant during the pre-2013 period, and it is 1.72 and significant at the 1% level during the post-2013 period. In light of the findings of Goldsmith-Pinkham et al. (2023), a larger and more significant coefficient during the post-2013 period is consistent with our baseline estimates being associated with climate risk.

We also test whether our findings are driven by periods of high climate news coverage. We define a month as a high (low) climate news month if the climate news index in that month is above (below) its median during our sample period. In Table 4, Column (3) shows that the coefficient estimate on *Climate News Sensitivity* is 1.13 when estimated during low climate news periods, and 1.67 when estimated during high climate news periods. It appears that *Climate News Sensitivity* has a greater influence on yield spreads when climate change-related issues have greater news coverage. This finding is consistent with investor attention to climate change influencing the pricing of climate change-related risks (Baldauf, Garlappi, and Yannelis (2020)).

The findings in this section show that the influence of *Climate News Sensitivity* on *Yield Spread* is time-varying, and this variation appears to be associated with the sentiment around climate change. We further explore this sentiment-based variation in our findings in Section 3.5. In the next section, we study the cross-sectional variation in our baseline finding by bond characteristics.

3.4. Variation in the Baseline Findings by Bond Maturity and Credit Risk

In this section, we examine whether our baseline findings vary predictably based on the exposures of municipal bonds to climate risk. We expect our baseline estimates to be more pronounced among longer term bonds and riskier bonds. This is because climate change is a long-run risk that would more negatively impact bonds with marginal credit quality.

To test these predictions, we include the interactions of *Climate News Sensitivity* with *Log(Time to Maturity)* and *Rating Number* in Columns (1) and (2) of Table 5, respectively. *Rating Number* is a numerical rating that corresponds to a bond's median rating from S&P, Fitch, and Moody's (e.g., AAA = 22, AA+ = 21, AA = 20). In Column (2), we include *Rating Number* as an additional variable and exclude rating dummies. We exclude *City Financials* in this test as these variables may be correlated with *Rating Number*, influencing the coefficient estimate on the *Rating Number* and *Climate News Sensitivity* interaction.

Column (1) of Table 5 shows that the coefficient estimate on the *Log(Time to Maturity)* and *Climate News Sensitivity* interaction is 0.90, and it is significant. This suggests that the influence of *Climate News Sensitivity* on *Yield Spread* is more positive (i.e., the baseline result is more pronounced) among longer term bonds, which are expected to be more sensitive to news about climate change. Compared to a city with the lowest *Climate News Sensitivity* (−3.92), a city with the highest *Climate News Sensitivity* (4.83) faces an additional 5 bps increase in yield spreads when doubling the maturity of its bonds ($0.05 = \log(2)\times(4.83-(-3.93))\times0.90/100$). As a caveat, the coefficient estimate on the interaction term is marginally significant, perhaps because there are strong maturity clienteles in the municipal bond market that contaminate the differential influence of municipal bonds' climate news sensitivity on yield spreads of short- and long-term municipal bonds (e.g., Kidwell and Koch (1983)).

In Column (2) of Table 5, we find that the coefficient estimate on the interaction term between *Rating Number* and *Climate News Sensitivity* is −0.46 and significant at the 5% level. This suggests that the influence of *Climate News Sensitivity* on *Yield Spread* is less (more) positive among safer (riskier) bonds. Relative to a city with the lowest *Climate News Sensitivity*, a city with the highest *Climate News Sensitivity* experiences an extra 4 bps increase in yield spreads for a one-notch lower rating ($0.04 = -1 \times (4.83 - (-3.93)) \times -0.46/100$). Consistent with climate risk being more material for bonds with marginal credit quality, this finding shows that the influence of *Climate News Sensitivity* on *Yield Spread* is more pronounced for bonds with lower ratings.

3.5. Understanding the Determinants of Climate News Sensitivities

Our findings in the previous sections provide suggestive evidence that our baseline findings are associated with climate risk exposures of municipal bonds. We now examine the determinants of *Climate News Sensitivity* to better understand its connection with climate risk. For ease of interpretation, we standardize the independent variables of interest in this section to have a standard deviation of one.

3.5.1. Cities' Physical Climate Risk Exposures and Climate News Sensitivities

We begin by studying whether *Climate News Sensitivity* is a function of cities' physical climate risk exposures in Table 6. As higher *Climate News Sensitivity* indicates greater exposure to climate risk, we hypothesize that there is a positive relationship between a city's climate risk exposure and *Climate News Sensitivity*. Because some cities issue many more municipal bonds than others, we run all the tests as equal-weighted regressions, weighted by the inverse of the number of bonds, and weighted by the inverse of the city's (log) assets. We report the traditional equal-weighted regressions in the table and leave the similar weighted regression results untabulated.

Our first climate risk proxy is Hallegatte et al. (2013)'s sea level rise exposure measure. This measure, which has been used in the literature as a climate risk proxy (e.g., Painter (2020), Tran and Uzmanoglu (2023)), is the predicted annual loss (as a percentage of a city's GDP) from a 40 cm sea level rise. *Sea Level Rise Exposure* is available for 61% of the observations and 14 cities in our sample and has a mean (standard deviation) of 0.11 (0.19).

Column (1) of Table 6 reports the results from a regression of *Climate News Sensitivity* on *Standardized Sea Level Rise Exposure*. We find that controlling for *Bond Characteristics*, *Beta Estimates*, and *City Financials*, the coefficient estimate on *Standardized Sea Level Rise Exposure* has the expected positive sign, but it is statistically insignificant. This finding suggests that the influence of *Climate News Sensitivity* on *Yield Spread* that we report in this paper is distinct from the positive relationship between sea level rise exposures of cities and the offering yield spreads on their new bond issues reported by Painter (2020). We further confirm this conclusion in Section 4 by showing that our baseline finding is robust to including *Sea Level Rise Exposure* as an additional control.

Because *Sea Level Rise Exposure* is missing for the majority of cities in our sample, we use the climate damage estimates of Hsiang et al. (2017) as an alternative proxy for cities' economic exposure to climate risk. The authors estimate total economic damages for each county as a percent of the county's income by incorporating climate science, econometric analyses, and process models. In our sample, the average (standard deviation) of these relative costs—*Climate Damages*—estimated using the 95th percentile assumption for sea level rise is 6.03% (5.26%).

Column (2) of Table 6 reports the results from a regression of *Climate News Sensitivity* on *Standardized Climate Damages* and shows that the coefficient estimate on *Standardized Climate Damages* is 0.04 and statistically significant at the 5% level. A one-standard deviation increase in climate damages is associated with a 0.04 increase in climate news sensitivity, which is about 18% of the absolute value of the average climate news sensitivity in our sample (018 = 0.04/0.22). This finding provides evidence that *Climate News Sensitivity* is positively correlated with the economic exposure of cities to climate risk.

We next investigate whether *Climate News Sensitivity* is associated with a city's history of flooding, instead of the expected costs in the future. For this purpose, we collect the number of flood instances in each city between January 1950 and July 2017 from the Urban Adaptation Assessment's (UAA's) website. The UAA constructs these statistics at the city level using the National Oceanic and Atmospheric Administration (NOAA) Storm Events Dataset. We also obtain the number of coastal flood instances, given that sea level rises associated with climate change would be more likely to increase coastal floods. The number of flood instances is available for 42,110 observations. Within our sample, there are on average about 52 flood and 7 coastal flood incidences reported in cities since 1950.

We find in Column (3) of Table 6 that the coefficient estimate on *Log(1+Standardized Number of Flood Instances)* is 0.20 and statistically significant. This suggests that cities that are more susceptible to floods have higher climate news sensitivities. As cities' cost of borrowing is positively associated with their climate news sensitivities, this finding is consistent with cities with greater climate risk exposures having higher borrowing costs.

Furthermore, Column (4) of Table 6 shows that the coefficient estimate on *Log(1+Standardized Number of Coastal Flood Instances)* is 0.27, which is larger than that on *Log(1+Standardized Number of Flood Instances)*. These estimates suggest that cities' climate news sensitivities, in particular, reflect their historical exposures to coastal flooding. To put this estimate into perspective, a one-standard deviation increase in the average number of *Standardized Coastal Flood Instances* (1.24) in our sample is associated with a 0.10 increase ($0.10 = 0.27 \times (\log(1+1.24+1) - \log(1+1.24))$) in climate news sensitivity. This translates into a 45% increase in the absolute value of the average climate news sensitivity in our sample ($0.45 = 0.10/0.22$).

3.5.2. Cities' Demographic Characteristics and Climate News Sensitivities

Having established the relation between cities' physical climate risk exposures and climate news sensitivities, we now study how the demographic characteristics of cities influence their climate news sensitivities. One of the drivers of the economic impact of climate change events is the population density in the affected areas. Cities with greater population densities would have greater number of people and critical infrastructure exposed to climate risk. We obtain population densities of cities, defined as the number of people per square kilometer, from the UAA's website. The UAA compiles this statistic using data from the U.S. Census as of 2015. The most densely populated cities in our sample are New York NY, Jersey City NJ, and Boston MA; the least densely populated cities in our sample are Chesapeake VA, Peoria AZ, and Oklahoma City OK.

We find in Column (5) of Table 6 that the coefficient estimate on *Log(Standardized Population Density)* is 0.06 and marginally significant with a p-value of 0.10. This finding suggests that cities with greater population densities have higher climate news sensitivities and higher climate risk induced borrowing costs, as there is a positive relation between municipal bond yield spreads and climate news sensitivities.

Next, we study the influence of poverty on *Climate News Sensitivity*. Poverty is an important factor that influences cities' economic exposures to climate risk, because insufficient financial resources put households living in poverty at greater risk of being adversely affected by natural disasters. We obtain information on the percent of a city's population in poverty from the UAA's website, which collects this statistic from the U.S. Census. The cities with the highest (lowest) poverty rates in our sample are Detroit MI, Hartford CT, and Springfield MA (Frisco TX, Scottsdale AZ, and Berkeley CA).

In Column (6) of Table 6, we find that the coefficient estimate on *Standardized Percent of Population in Poverty* is 0.09 and significant. This finding indicates that cities with higher poverty rates have higher climate news sensitivities. In other words, prices (cost of borrowing) of bonds issued by cities with higher poverty rates would decline (increase) more in response to negative climate change news. For an average size ($33.8 million) bond issue, a one standard deviation increase in poverty is associated with an abnormal increase in annual interest expenses for cities ranging between $400 ($0.04\times10^{-2} = 1.40\times0.09\times33.8/10{,}000$) and $2,700 ($0.27\times10^{-2} = 8.99\times0.09\times33.8/10{,}000$). These interest expenses per bond can aggregate to economically significant values, as the total municipal bonds outstanding in the U.S. exceeded $4 trillion in 2021.[9] Our findings have important policy implications, as they suggest that cities with higher poverty rates would also be disproportionately affected by climate change.

In addition, we investigate how the beliefs of the citizens in a city regarding climate change influence the sensitivity of the city's bond prices to climate news. Local preferences may influence the pricing of municipal bonds, as there is evidence of segmentation in the municipal bond market (e.g., Hendershott and Kidwell (1978); Kidwell, Koch, and Stock (1984); Schultz (2012)). We obtain the percentage of adults who believe climate change is already harming people in the U.S. (or will be harming people in the U.S. within 10 years) as of 2014, from the Yale Project on Climate Change Communication, which we obtain from the UAA's website.

The average *Percentage of Adults Believing in Global Warming* in our sample is 51.87%. This ratio has a standard deviation of 4.24%, indicating that people's beliefs about climate risk vary geographically. In Column (7) of Table 6, we report that the coefficient estimate on *Standardized Percentage of Adults Believing in Global Warming* is 0.15 and significant. This

[9] According to the statistics compiled by the Securities Industry and Financial Markets Association (SIFMA) Research (https://www.sifma.org/resources/research/us-municipal-bonds-statistics/)

finding suggests that municipal bond prices react more negatively to climate change news if the local investor base believes climate change is harmful. Consistent with the findings of Baldauf, Garlappi, and Yannelis (2020) from studying real estate prices, our finding shows that investor beliefs influence the degree to which climate change is priced.

We next relate the percentage votes that Democratic candidates in presidential elections receive during our sample period to *Climate News Sensitivity*. The intuition is that cities that lean more Democrat are more likely to be receptive to environmental issues. We obtain this information at the county level from the Massachusetts Institute of Technology (MIT) Election Data and Science Lab. The average of *Percent Voted Democrat* is 73.63%. This skew is expected as larger metropolitan areas, whose residents tend to be aligned with the Democratic party, contribute more observations to the sample. The correlation coefficient between *Percent Voted Democrat* and *Percentage of Adults Believing in Global Warming* is close to 0.90, further supporting the notion that more democratic cities house adults who are more likely to care about climate change.

Column (8) of Table 6 shows that the coefficient estimate on *Standardized Percent Voted Democrat* is 0.13 and significant. A one-standard deviation increase in *Percent Voted Democrat* is associated with a 0.13 higher *Climate News Sensitivity*. Consistent with our earlier result, this finding suggests that beliefs and attitudes toward climate change are drivers of cities' financial exposure to climate change.

3.5.3. Cities' Transition Risk Exposures and Climate News Sensitivities

We next examine the relationship between transition risk and *Climate News Sensitivity*. To do so, we test whether *Climate News Sensitivity* is higher for issuers located in states with greater economic dependence on high carbon emission industries. These states would have greater transition risk as zero carbon emission policies would be costlier for them to adopt. Our proxy for this carbon intensity of the economy is the natural logarithm of metric tons of carbon emissions in a state divided by the dollar value of the state's GDP (CO_2/GDP). We collect this information for each state and year from the U.S. Energy Information Administration's website.[10]

One concern with this measure is that it is highly correlated with what local residents believe about climate change, which influences *Climate News Sensitivity*. High carbon intensity states are likely to be the ones whose residents believe climate change is not harmful. Consistent with this prediction, we find that the correlation coefficient between our measure of carbon intensity of the economy and *Percentage of Adults Believing in Global Warming* is −0.74. We break this correlation by orthogonalizing the natural logarithm of the CO_2/GDP measure with respect to *Percentage of Adults Believing in Global Warming*, and use this as our proxy for *Carbon Intensity of the Economy*.

Column (9) of Table 6 shows that the coefficient estimate on *Standardized Carbon Intensity of the Economy* is 0.08 and significant. This positive coefficient estimate indicates that municipal bonds issued in states with higher *Carbon Intensity of the Economy* have higher *Climate News Sensitivity*, which predicts greater financial exposure to climate change. Our finding suggests that *Climate News Sensitivity*, in addition to the physical risk, also reflects the transition risk associated with climate change.

To summarize the findings of this section, climate change is likely to lead to a larger increase in borrowing costs of cities with greater physical and transition risks of climate change, and higher population density and poverty rates. There is also evidence that local investors' climate change beliefs influence the effect climate change has on cities' borrowing costs.

[10] https://www.eia.gov/environment/emissions/state/. In each year during our analysis period, we rank states based the carbon intensity of their economies. The states that are ranked within the top (bottom) of these lists are Wyoming, North Dakota, Louisiana, West Virginia, and Kentucky (New Hampshire, Washington, California, Vermont, Connecticut, New York, and District of Columbia).

3.6. Evidence from the Primary Municipal Bond Market

Our tests so far use secondary market transactions to estimate the effect of climate news on yield spreads of municipal bonds. These bonds are relatively liquid by our empirical design: they are traded in the observation month to allow for the computation of their yield spreads, and they trade frequently enough for us to compute their climate news sensitivities. This empirical design raises the possibility that our findings apply only to liquid bonds. The results of several robustness tests in Section 4 address this concern. For additional evidence, both to address liquidity concerns and to support our baseline findings, here we also study the influence of climate news sensitivity on at-issuance yield spreads on new bond issues *regardless of their post-issuance liquidity levels*.

We identify the new bonds issued by our sample of 104 cities and obtain bond characteristics (e.g., offering price, coupon rate, maturity) and city characteristics (e.g., assets, net income, liabilities) as of the issue date from Bloomberg. We then compute offering yields and yield spreads following the same methodology described in Section 2, and winsorize the continuous variables at the 1st and 99th percentiles in each year as before.

Our new issues sample includes 18,973 bonds issued by 102 cities. The average offering yield spread is 0.52% with a standard deviation of 1.20%. New bond issuances are unbalanced through months, so we run an OLS regression of offering yield spreads instead of a Fama-MacBeth model. Our regression equation is as follows:

$$Offering\ Yield\ Spread_i = \alpha + \alpha_{Issue\ Year\text{-}Month} + \beta Average\ Climate\ News\ Sensitivity_j + X'_{i,t}\gamma + \varepsilon_i \quad (5)$$

where *Offering Yield Spread*$_i$ is the difference between the offering yield of municipal bond *i* and the yield on a maturity matched Treasury bond on the issue date (*t*), $\alpha_{Issue\ Year\text{-}Month}$ is the issue year-month fixed effects, *Average Climate News Sensitivity*$_j$ is the average of climate news sensitivities on issuer *j*'s bonds, and $X_{i,t}$ is a vector of control variables. We use a city-level climate news sensitivity measure (average of climate news sensitivities on a city's traded bonds) because new bond issues do not have a trading history to estimate their own climate news sensitivities. We cluster standard errors at the issuer level when computing *t*-values.

Columns (1) through (4) in Table 7 report the coefficient estimate on *Average Climate News Sensitivity* while expanding the list of controls incrementally in each column, as in Table 2. We find that the coefficient estimate on *Average Climate News Sensitivity* is positive and significant in all specifications. With the full set of controls, Column (4) reports a coefficient estimate of 2.40, suggesting that a one-standard deviation (0.95) increase in *Average Climate News Sensitivity* is associated with an increase of 4.38 percent (4.38 = 2.40×0.95/0.52) in average offering yield spreads. This estimate, which is within the range of estimates from studying secondary market trades, provides additional support for the positive relation between the climate news sensitivity of issuers and their cost of borrowing in the municipal bond markets, and addresses the concern that our findings are relevant only for liquid bonds.

3.7. Investigating the Demand for Hedging Mechanism

If investors dynamically trade municipal bonds to hedge climate risks, municipal bonds with higher climate news sensitivities would face a greater hedging demand, increasing their prices and lowering their yield spreads (e.g., Bali, Brown, and Tang (2017)). Therefore, *Climate News Sensitivity* may be priced in municipal yield spreads through investors' demand for hedging climate risks. We use the segmented nature of the municipal bond market to examine whether this hedging demand mechanism is at play.

Municipal bonds are typically exempt from state income taxes for investors who live in the issuer's state. This tax benefit makes municipal bonds attractive to local investors (e.g., Hendershott and Kidwell (1978); Kidwell, Koch, and Stock (1984); Schultz (2012)). Accordingly, tax exempt municipal bonds that are issued in states with income taxes would have a smaller investor base compared to the remaining bonds.[11] Assuming that size of the investor base is positively correlated with the hedging demand, the hedging demand mechanism predicts a more pronounced relationship between *Climate News Sensitivity* and *Yield Spread* among municipal bonds that have a larger investor base.

We run our baseline regression of *Yield Spread* (Column (4), Table 2) separately using a sample of state tax exempt municipal bonds that are issued in states with income taxes (i.e., local investor base) and the remaining municipal bonds in our sample (i.e., global investor base). In line with the prediction of the hedging demand mechanism, Table 8 reports that the coefficient estimate on *Climate News Sensitivity* is more positive in the case of a global investor base (1.56 in Column (1)) compared to a local investor base (1.44 in Column (2)). Although the difference in these coefficient estimates is not statistically significant, its direction provides suggestive evidence that climate risks may be priced in the municipal bond market through a hedging mechanism, consistent with the findings of Huynh and Xia (2021) from studying corporate bonds.

3.8. Policy Implications

In this paper, we demonstrate that a higher climate news sensitivity is associated with a higher cost of borrowing for cities. A natural question that arises is whether cities can mitigate this effect. Our findings in Sections 3.4 and 3.5 suggest how cities can manage their financial exposures to climate change. However, it is important to note that the partial correlations reported in these sections do not imply causality. The policy implications discussed here are intended to offer guidance for future researchers.

[11] The states with no income taxes are Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming.

First, it appears that cities may mitigate their financial exposures to climate change by shortening the maturity of their debt. This response makes economic sense because climate change is a long-term risk. However, a shorter debt maturity would increase the rollover risk. An alternative approach would be to enhance the credit quality of municipal bonds, as the yield spreads on bonds with better credit ratings are less sensitive to their climate news sensitivities.

Cities may attempt to manage their climate risk exposures by engaging in activities that would lower their climate news sensitivities and overall improve their resilience to both physical and transition risks of climate change. For instance, infrastructure improvements that would prevent flooding may lower their climate news sensitivities, as a fewer number of flood incidences is associated with a lower climate news sensitivity. As higher population density is associated with higher climate news sensitivity, city officials may also implement zoning changes that promote lower residential density, especially in high climate risk areas, to mitigate their cities' economic exposure to climate change. By the same token, transitioning to a less carbon-dependent economy, and reducing the population's exposure to climate-related risks may help cities lower their climate news sensitivities.

To the extent that security prices reflect the beliefs of the marginal investor, we provide some indirect evidence that the marginal investor in municipal markets may be a climate change skeptic. We show that the extent to which cities' cost of borrowing is influenced by climate change depends on the beliefs of their residents regarding the reality of climate change. The more local investors do not believe in climate change, the longer cities may delay experiencing the negative impacts of climate change on their borrowing costs. Future researchers may shed light on the causality of these claims and assist in formulating a policy path for cities to mitigate their financial exposures to climate risk.

4. Robustness Tests

The conclusions from our baseline finding reported in Column (4) of Table 4 are robust to many alternative empirical specifications. We summarize the results of these alternative specifications graphically in Figure 1 and provide more detail of these tests in Appendix E. We begin by examining whether using longer lags in adjusting standard errors influences our findings. Our baseline regression uses Newey-West adjusted standard errors with 3-month lags to correct for the potential correlation in errors. Regressions (1), (2), and (3) in Appendix E show that our findings are robust to adjusting standard errors using Newey-West standard errors with 6-month, 9-month, and 12-month lags, respectively.

Petersen (2009) reviews the methods for estimating standard errors in panel datasets and shows that Newey-West adjusted standard errors in Fama-MacBeth regressions can be biased. However, he finds that cluster-corrected standard errors from OLS regressions are unbiased, as they account for the within-firm dependence in errors. To determine whether within-issuer dependence in errors biases our findings, we compare our estimates from the earlier Fama-MacBeth regressions with those from an OLS regression model.

Regression (4) reports the coefficient estimate on *Climate News Sensitivity* from an OLS regression of yield spreads with all the controls in our baseline model and trade year-month fixed effects. The standard errors are clustered at the issuer level to account for correlation in errors within cities. We find that the coefficient estimate on *Climate News Sensitivity* remains positive and significant in this alternative estimation approach.

Next, we study the influence of potential outlier observations on our findings. In our baseline regressions, we winsorize all of the continuous variables at the 1st and 99th percentiles in each year. Regression (5) reports the results using non-winsorized variables. We find that the coefficient estimate on *Climate News Sensitivity* is 8.99 and statistically significant. This coefficient estimate is much larger than our baseline estimate of 1.40, suggesting that extreme observations result in a stronger estimate of the relationship between *Climate News Sensitivity* and *Yield Spread*.

When we estimate *Climate News Sensitivity* in Equation (1), we control for excess stock market returns to account for the sensitivity of municipal bond returns to market news. As municipal bonds may be more sensitive to news about municipal bond markets, we replace excess stock market returns with excess municipal bond market returns when estimating *Climate News Sensitivity*. We define excess municipal bond returns as the difference in monthly returns of the S&P Municipal Bond Index and one-month Treasury bill.

We find that the average *Municipal Bond Market Beta* is 0.78, which is, as expected, larger than the average *Stock Market Beta*. Consistent with our baseline estimate, Regression (6) shows that the coefficient estimate on *Climate News Sensitivity* is positive and significant when it is estimated using excess municipal bond returns and controlling for *Municipal Bond Market Beta*. Accordingly, our findings are robust to using stock or municipal bond market returns to account for the public information set.

In Section 3.5, we show that *Climate News Sensitivity* is associated with the physical climate risk exposures of cities. This raises the question of whether *Climate News Sensitivity* captures the physical exposures of cities climate risk already reported in the literature (e.g., Painter (2020)), or it is an incremental factor. To answer this question, we control for the sea level rise measure of Hallegatte et al. (2013) and the climate damage estimates of Hsiang et al. (2017) as additional variables in our regressions. Regressions (7) and (8), respectively, show that controlling for these sea level rise and climate damage estimates does not materially influence the coefficient estimate on *Climate News Sensitivity*. This finding provides evidence that our study identifies a new climate risk-related covariate that is associated with cities' cost of borrowing.

We next run a series of robustness tests using alternative control variables and samples. In Regressions (9) and (10), we use *Amihud* and *Percent of Traded Days*, respectively, as alternative bond liquidity measures. In Regressions (11) and (12), we control for *Percentage of Adults Believing in Global Warming* and *Percent Voted Democrat* as additional controls, respectively, to see whether our findings are solely driven by local beliefs about climate change. To examine the influence of state taxes on our findings, we first restrict our sample to tax-exempt bonds in Regression (13). We then control for the state income tax rate applicable to the highest income bracket in Regression (14).[12] Additionally, we control for this state income tax rate and its interaction with *State Tax Exemption Dummy* in Regression (15). The samples in Regressions (16), (17), and (18) include bond trades executed during the last 10 days of a month, bonds without credit enhancements, and liquid bonds defined as those traded more frequently than the median bond (seven transactions) in our sample during the month before an observation date, respectively. We find that the coefficient estimate on *Climate News Sensitivity* is positive and significant in all of these specifications, consistent with our baseline estimates.

The next robustness tests in this section involve our primary dependent variable. In our baseline regressions, we define *Yield Spread* as the difference in yields on municipal bonds and maturity-matched Treasury bonds. Alternatively, we use yield spreads computed over the Zero Treasury Curve, the USD Swap Curve, and the AAA-Rated Municipal Bond Market Curve in Regressions (19), (20), and (21), respectively. As before, we linearly interpolate the benchmark

[12] Using the average tax rate or that of the lowest income bracket does not influence the results. We obtain historical tax rate data from https://www.taxpolicycenter.org/statistics/state-individual-income-tax-rates.

rate if an exact maturity match is unavailable. Appendix B provides detailed descriptions of these alternative yield spreads. We find that the coefficient estimates on *Climate News Sensitivity* are positive and significant using these alternative yield spread measures as dependent variables.

We also examine the robustness of our findings to an alternative climate news index. The primary climate news innovation index used in this paper captures the increased climate change reporting in the WSJ. The logic for using this as the primary proxy is that climate change generally captures the media's attention when there is a concern. This news index, however, may capture both positive and negative news about climate change. To address this concern, we also use the explicitly negative (adverse) climate news index that Engle et al. (2020) construct using the Crimson Hexagon's negative sentiment climate change news data. One disadvantage of this index is that it is available since June 2008.

In Regression (22), we report the results from our baseline Fama-MacBeth regression of *Yield Spread* controlling for *Alternative Climate News Sensitivity*, which is estimated using the innovations in the negative climate news index of Engle et al. (2020). This regression also controls for *Stock Market Beta*, *Credit Spread Beta*, and *Term Spread Beta* estimated along with *Alternative Climate News Sensitivity*. Consistent with our baseline estimates, we find that the coefficient estimate on *Alternative Climate News Sensitivity* is positive and significant, and falls within the range of the influence *Climate News Sensitivity* has on yield spreads, as reported in Section 3.1.[13]

In Regressions (23), (24), and (25), we use our initial sample of 240 cities, 107 cities with populations of at least 100,000, and 157 cities with populations of at least 50,000, respectively. Our baseline specification also requires cities to contribute multiple bonds to the sample. Here we

[13] We find in untabulated regression results that the coefficient estimate on *Alternative Climate News Sensitivity* is positive but statistically insignificant when estimated using winsorized variables. It appears that extreme values of climate news sensitivities drive the relation between *Alternative Climate News Sensitivity* and *Yield Spread*.

do not impose the same requirement for robustness purposes. We find that the coefficient estimates on *Climate News Sensitivity* are positive and significant in these alternative samples of cities.

Overall, Figure 1 and Appendix E show that the coefficient estimates on *Climate News Sensitivity* are positive and significant in various empirical specifications. This section demonstrates that our findings are robust to alternative empirical specifications.

5. Conclusion

The literature shows that municipalities with greater exposures to sea level rises and heat stress have higher cost of borrowings (e.g., Painter (2020); Goldsmith-Pinkham et al. (2023); Acharya et al. (2023)). In addition to this physical climate risk, however, transition risk arising from regulatory and technological changes associated with climate policies may also influence local economies (e.g., Giglio, Kelly, and Stroebel (2021); Bolton and Kacperczyk (2023)). Accordingly, physical climate risk measures alone may over or under estimate the climate risk exposures of municipalities.

We estimate the climate news sensitivities of municipal bonds and invert their signs. This way, we expect bonds with higher (lower) climate news sensitivities to be affected more (less) negatively from future negative climate news. We find that climate news sensitivities are positively associated with yield spreads. The effect is economically meaningful: a one-standard deviation increase in climate news sensitivity is associated with an increase of between 1.74% and 11.19% in average yield spreads. This finding demonstrates that higher climate risk exposure is associated with higher cost of borrowing.

It is useful to compare our basic result to others in the literature because of the possibility that physical climate risk measures can over- or under- estimate the climate risk exposures of municipalities. Our point estimates suggest that on average, our market-based measure and the physical-only measures yield comparable results: we find that a one standard deviation change in our market-based measure climate risk relates to up to a 11.19% increase in yield spreads, while existing studies report a 1.24% increase in yields on long-term bonds (Painter (2020)), a 8.84% increase in average yield spreads (Goldsmith-Pinkham et al. (2023)), or a 7.27% increase in average yield spreads (Acharya et al. (2023)) based on physical climate risk measures. Aside from the differences in the overall "headline" results, we know from our analysis that there is substantial variation in climate risk based on cities' demographics, such as poverty, population density, and climate science acceptance.

Our findings contribute to the asset pricing literature by demonstrating a new mechanism through which climate risk is priced in the municipal bond market. They also carry important policy implications, highlighting that cities with certain characteristics, such as those with higher poverty rates, are disproportionally affected by climate change.

References

Acharya, Viral V., Tim Johnson, Suresh Sundaresan, and Tuomas Tomunen, 2023, Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress, Working Paper, *New York University*.

Amihud, Yakov, 2002, Illiquidity and Stock Returns: Cross-Section and Time-Series Effects, *Journal of Financial Markets* 5: 31–56.

Ang, Andrew, Vineer Bhansali, and Yuhang Xing, 2014, The Muni Bond Spread: Credit, Liquidity, and Tax, *Columbia Business School Research Paper*, 14–37.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does Climate Change Affect Real Estate Prices? Only If You Believe in It, *Review of Financial Studies* 33: 1256–1295.

Bali, Turan G., Stephen J. Brown, and Yi Tang, 2017, Is Economic Uncertainty Priced in the Cross-Section of Stock Returns? *Journal of Financial Economics* 126: 471−489.

Bernstein, Asaf, Matthew T. Gustafson, and Ryan Lewis, 2019, Disaster on the Horizon: The Price Effect of Sea Level Rise, *Journal of Financial Economics* 34: 253−272.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global Pricing of Carbon Transition Risk, *Journal of Finance* 78: 3677–3754.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang, 2022, Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits, *Quarterly Journal of Economics* 137: 2037–2105.

Choi, Darwin, Zhenyu Gao, and Wenxi Jiang, 2020, Attention to Global Warming, *Review of Financial Studies* 33: 1112−1145.

Cornaggia, Kimberly, John Hund, Giang Nguyen, and Zihan Ye, 2022, Opioid Crisis Effects on Municipal Finance, *Review of Financial Studies* 35: 2019−2066.

Engle, Robert F., Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging Climate Change News, *Review of Financial Studies* 33: 1184−1216.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy* 81: 607–636.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33: 3–56.

Gao, Pengjie, Chang Lee, and Dermot Murphy, 2020, Financing Dies in Darkness? The Impact of Newspaper Closures on Public Finance, *Journal of Financial Economics* 135: 445–467.

Giglio, Stefano, Bryan Kelly, and Johannes Stroebel, 2021, Climate Finance, *Annual Review of Financial Economics* 13: 15–36.

Goldsmith-Pinkham, Paul S., Matthew Gustafson, Ryan Lewis, and Michael Schwert, 2023, Sea Level Rise Exposure and Municipal Bond Yields, *Review of Financial Studies*, Forthcoming.

Green, Richard C., Dan Li, and Norman Schürhoff, 2010, Price Discovery in Illiquid Markets: Do Financial Asset Prices Rise Faster than They Fall? *Journal of Finance* 65: 1669–1702.

Hallegatte, Stephane, Colin Green, Robert J. Nicholls, and Jan Corfee-Morlot, 2013, Future Flood Losses in Major Coastal Cities, *Nature Climate Change* 3: 802–806.

Hallegatte, Stephane, Mook Bangalore, Laura Bonzanigo, Marianne Fay, Ulf Narloch, Julie Rozenberg, and Adrien Vogt-Schilb, 2014, Climate Change and Poverty – An Analytical Framework, World Bank Policy Research Working Paper No. 7126.

Hendershott, Patric H., and David S. Kidwell, 1978, The Impact of Relative Security Supplies: A Test with data from a Regional Tax-Exempt Bond Market, *Journal of Money, Credit and Banking*, 10: 337–347.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, Kate Larsen, and Trevor Houser, 2017, Estimating Economic Damage from Climate Change in the United States, *Science* 356: 1362–1369.

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

Kidwell, David S., and Timothy W. Koch, 1983, Market Segmentation and the Term Structure of Municipal Yields, *Journal of Money, Credit and Banking* 15: 40–55.

Kidwell, David S., Timothy W. Koch, and Duane R. Stock, 1984, The Impact of State Income Taxes on Municipal Borrowing Costs, *National Tax Journal* 37: 551–561.

Lesk, Corey, Pedram Rowhani, and Navin Ramankutty, 2016, Influence of Extreme Weather Disasters on Global Crop Production, *Nature* 529: 84–87.

Litterman Robert, Clark E. Anderson, Nathaniel Bullard, et al., 2020, Report of the Climate-Related Market Risk Subcommittee, Market Risk Advisory Committee of the U.S. Commodity Futures Trading Commission, Washington, DC.

Newey, Whitney K., and Kenneth D. West, 1987, Hypothesis Testing with Efficient Method of Moments Estimation, *International Economic Review*, 777–787.

Nguyen, Duc D., Steven Ongena, Shusen Qi, and Vathunyoo Sila, 2022, Climate Change Risk and the Cost of Mortgage Credit, *Review of Finance* 26: 1509−1549.

Nordhaus, William D., 1977, Economic Growth and Climate: The Carbon Dioxide Problem, *American Economic Review* 67: 341–346.

Nordhaus, William D., 2019, Climate Change: The Ultimate Challenge for Economics, *American Economic Review* 109: 1991–2014.

Painter, Marcus, 2020, An Inconvenient Cost: The Effect of Climate Change on Municipal Bonds, *Journal of Financial Economics* 135: 468−482.

Park, Jisung, Stephane Hallegatte, Mook Bangalore, and Evan Sandhoefner, 2018, Households and Heat Stress: Estimating the Distributional Consequences of Climate Change, *Environment and Development Economics* 23: 349−368.

Petersen, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22: 435–480.

Raimi, Daniel, 2021, Mapping County-Level Exposure and Vulnerability to the US Energy Transition, Working Paper, *Resource for the Future*.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, Firm-Level Climate Change Exposure, *Journal of Finance* 78: 1449–1498.

Schultz, Paul, 2012, The Market for New Issues of Municipal Bonds: The Roles of Transparency and Limited Access to Retail Investors, *Journal of Financial Economics* 106: 492–512.

Schwert, Michael, 2017, Municipal Bond Liquidity and Default Risk, *Journal of Finance* 72: 1683–1722.

Skoufias, Emmanuel, Mariano Rabassa, and Sergio Olivieri, 2011, The Poverty Impacts of Climate Change: A Review of the Evidence, World Bank Policy Research Working Paper No. 5622.

Stern, Nicholas, 2008, The Economics of Climate Change, *American Economic Review* 98: 1–37.

Stroebel, Johannes, and Jeffrey Wurgler, 2021, What Do You Think About Climate Finance? *Journal of Financial Economics* 142: 487–498.

Tran, Nhu, and Cihan Uzmanoglu, 2023, Climate Risk and Credit Ratings, *Journal of Financial Research*, Forthcoming.

Winsemius, Hessel C., Brenden Jongman, Ted I.E. Veldkamp, Stephane Hallegatte, Mook Bangalore, and Philip J. Ward, 2018, Disaster Risk, Climate Change, and Poverty: Assessing the

Global Exposure of Poor People to Floods and Droughts, *Environmental and Development Economics* 23: 328–348.

Appendix A. Sample Selection

This table summarizes the sample selection and clean-up steps. Some of the variables are downloaded from Bloomberg, which imposes monthly data download limits. To minimize the number of data points to be downloaded from Bloomberg, the sample is not constructed in the exact order below.

The estimation period is from January 2005 to June 2017, and the analysis period is from January 2010 to July 2017.
- Municipal Securities Transaction Data from MSRB through WRDS is available to us since January 2005.
- WSJ based climate change news innovation index of Engle et al. (2020) is available until June 2017.
- For each bond-month, climate news sensitivity is estimated using the previous 60 monthly returns.
- Estimated climate news sensitivities are available between January 2010 and July 2017.
Keep general obligation and fixed coupon bonds issued by cities in the U.S. mainland.
Keep observations with non-missing maturity date, coupon rate, trade price, and trade amount information.
Keep bonds with a single coupon rate and maturity date in the MSRB dataset.
Keep bonds with trading prices greater than $10.
Keep bonds with maturities between 1 and 100 years as of trade date.
Keep transactions with trade amounts greater than or equal to $5,000.
Keep bonds with coupon rates less than or equal to 20%.
If there are only two trades in a day, keep the prices on that day if they are within $20 of each other.
If there are more than two trades in a day, keep the bond prices that are within $20 of the median price on that day.
If the absolute value of the difference between the price on the previous trade date (pre-price) and the price on the next trade date (post-price) is within $5, keep the bond price on the trade date if the absolute value of the difference between the price on the trade date and average of pre- and post-prices is within $20.
For each bond and on each trade date, compute the daily weighted average yield to maturity where the weights are based on trade amounts.
Keep the latest daily observation for each bond in each month, creating a bond-month-level dataset.
Estimate the climate news sensitivity for each bond in each month using the monthly returns during the previous 60-month period. Require at least 30 monthly returns to estimate the climate news sensitivity.
Keep observations with available climate news sensitivity estimates and weighted average yields.
Keep cities with populations of at least 50,000 as of 2010.
Keep cities with multiple bonds in the sample.

Appendix B. Variable Definitions

This table provides the definitions and data sources of the variables used in the paper. All continuous variables are winsorized at the 1st and 99th percentiles in each year, unless indicated otherwise.

Variables	Definitions
Yield Spread (The Primary Dependent Variable)	The differences in yield to maturities of a municipal bond and a maturity-matched Treasury bond. If an exact match is unavailable, the linearly interpolated Treasury yields are used. The inputs to compute yield to maturities on municipal bonds are obtained from MSRB and Bloomberg, and the historical term structure of Treasury yields are obtained from the Treasury's website.
Climate News Sensitivity (The Independent Variable of Interest)	The coefficient on climate news (the WSJ based climate change news innovation index of Engle et al. (2020)), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for excess stock market return, term spread, and credit spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details. The sign of the coefficient on climate news innovation is inverted to associate a higher climate news sensitivity with a higher climate risk exposure.
Bond Characteristics	
Issue Amount	The issue amount of a municipal bond. Source: Bloomberg.
Time to Maturity	Bond maturity measured in years as of the trade date. Source: Bloomberg, MSRB.
Number of Trades	The total number of trades reported in the month before a trade date. Source: MSRB.
Competitive Offering Dummy	Indicates competitive bond offerings. Source: Bloomberg.
Federal Tax Exemption Dummy	Indicates whether a municipal bond is exempt from Federal taxes. Source: Bloomberg.
State Tax Exemption Dummy	Indicates state tax exempt municipal bonds. Source: Bloomberg.
Callable Dummy	Indicates whether a municipal bond is callable. Source: Bloomberg.
Sinking Fund Dummy	Indicates municipal bonds with sinking fund provisions. Source: Bloomberg.
Credit Enhancement Dummy	Indicates whether a municipal bond has credit enhancements. Source: Bloomberg.
AAA Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the AAA rating range. Source: Bloomberg.
AA Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the AA rating range. Source: Bloomberg.
A Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the A rating range. Source: Bloomberg.
BBB Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the BBB rating range. Source: Bloomberg.
BB Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the BB rating range. Source: Bloomberg.
B Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is within the B rating range. Source: Bloomberg.

Continued on the next page.

Appendix B continued.

Below B Rated Dummy	Indicates whether the median of a municipal bond's credit ratings from Moody's, S&P, and Fitch as of the trade date is below the B rating range. Source: Bloomberg.
Unrated Dummy	Indicates whether a municipal bond is not rated by Moody's, S&P, and Fitch as of the trade date. Source: Bloomberg.
Beta Estimates	
Stock Market Beta	The coefficient on excess stock market return (the difference between monthly returns of the stock market and one-month Treasury bill, Source: Kenneth French's website), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for climate news innovation, term spread, and credit spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details.
Term Spread Beta	The coefficient on the term spread (the difference in monthly returns of a 10-year Treasury bond and one-month Treasury bill, Source: Bloomberg, Kenneth French's website), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for climate news innovation, excess stock market return, and credit spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details.
Credit Spread Beta	The coefficient on credit spread of municipal bonds (the difference between monthly returns of BBB-rated municipal bonds and AAA-rated municipal bonds, Source: Bloomberg), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for climate news innovation, excess stock market return, and term spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details. Source:
City Financials	
Assets	A city's total assets obtained from the latest annual financial report prior to the trade date. Source: Bloomberg.
Net Income/Assets	A city's net income to total assets ratio obtained from the latest annual financial report prior to the trade date. Source: Bloomberg.
Cash/Assets	A city's cash and equivalents to total assets ratio obtained from the latest annual financial report prior to the trade date. Source: Bloomberg.
Liabilities/Assets	A city's total liabilities to total assets ratio obtained from the latest annual financial report prior to the trade date. Source: Bloomberg.
Other Variables	
Climate News Innovation	The WSJ based climate change news innovation index of Engle et al. (2020).
Rating Number	The median of credit ratings from Moody's, S&P, and Fitch as of the trade date. This median rating is converted into a numerical number that increases with credit quality (e.g., AAA = 22, AA+ = 21, AA = 20). Not winsorized. Source: Bloomberg.
Sea Level Rise Exposure	The expected annual loss of a city from a 40 cm sea level rise as a percentage of the city's GDP. Not winsorized. Source: Hallegatte et al. (2013).
Climate Damages	The 95th percentile estimate of climate damages to a county as a percentage of the county's GDP. Not winsorized. Source: Hsiang et al. (2017).
Number of Flood Instances	The number of flood events occurred in a city between January 1950 and July 2017. Not winsorized. Source: NOAA Storm Events Database, downloaded form UAA.

Continued on the next page.

Appendix B continued.

Number of Coastal Flood Instances	The number of coastal flood events occurred between January 1950 and July 2017. Not winsorized. Source: National Weather Services, downloaded from UAA.
Population Density	The number of people in a city per square kilometer, as measured in 2015. Not winsorized. Source: U.S. Census, downloaded from UAA.
Percent of Population in Poverty	Percent of a city's population that is in poverty as of 2015. Not winsorized. Source: U.S. Census, downloaded from UAA.
Percentage of Adults Believing in Global Warming	The percent of adults in a county who believe that global warming is harmful, as estimated in 2014. Not winsorized. Source: Yale Project on Climate Change Communication, downloaded from UAA.
Percentage Voted Democrat	The percent of population in a county voted democrat in presidential elections. Not winsorized. Source: MIT Election Data and Science Lab.
Carbon Intensity of the Economy	Natural logarithm of metric tons carbon emissions in a state divided by the dollar value of the state GDP. This variable is orthogonalized with respect to *Percentage of Adults Believing in Global Warming*, as they are highly correlated with a correlation coefficient of −0.73. Not winsorized. Source: U.S. Energy Information Administration.
Alternative Climate News Sensitivity	The coefficient on the negative (i.e., bad) climate news innovation index of Engle et al. (2020), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for excess stock market return, term spread, and credit spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details. The sign of the coefficient on negative climate news innovation is inverted to associate a higher climate news sensitivity with a higher climate risk exposure. Not winsorized.
Amihud	The median of daily Amihud (2002) liquidity measures in the month prior to the trade date. Following the methodology of Schwert (2017), daily Amihud measure is computed for each bond i on day t as: $$Amihud_{i,t}=\frac{1}{N_t}\sum_{j=1}^{N_t}\frac{\left\lvert\frac{P_j-P_{j-1}}{P_{j-1}}\right\rvert}{Q_j},$$ where N_t is the number of trades, j indicates a trade, and P_j and Q_j indicate the price and amount of the trade, respectively. Source: MSDA.
Percent of Traded Days	The ratio of the number of days with transactions to the number of trading days in the month prior to the trade date. Source: MSDA.
Municipal Bond Market Beta	The coefficient on excess municipal bond market return (the difference between monthly returns of the S&P Municipal Bond Index and one-month Treasury bill, Source: Bloomberg, Kenneth French's website), estimated by running a regression of monthly municipal bond returns minus monthly Treasury bill returns. This regression also controls for climate news innovation, term spread, and credit spread. The estimation period is 60 months and the sensitivities are estimated for each bond-month on a rolling-window basis. See Equation (1) for details.
Yield Spread Over Zero Treasury Curve	Yield spread computed using the Zero Treasury Curve as the benchmark. Source: MSDA, Bloomberg.
Yield Spread Over Swap Curve	Yield spread computed using the USD Swap Curve as the benchmark. Source: MSDA, Bloomberg.
Yield Spread Over AAA-Rated Municipal Bond Curve	Yield spread computed using the AAA-Rated U.S. Municipal Bond Curve as the benchmark. Source: MSDA, Bloomberg.
Local Dummy	Indicates bonds that are exempt from state taxes, and issued in states with income taxes. These states include all U.S. states except Alaska, Florida, Nevada, New Hampshire, South Dakota, Tennessee, Texas, Washington, and Wyoming.

Appendix C. List of Cities with Climate News Sensitivities

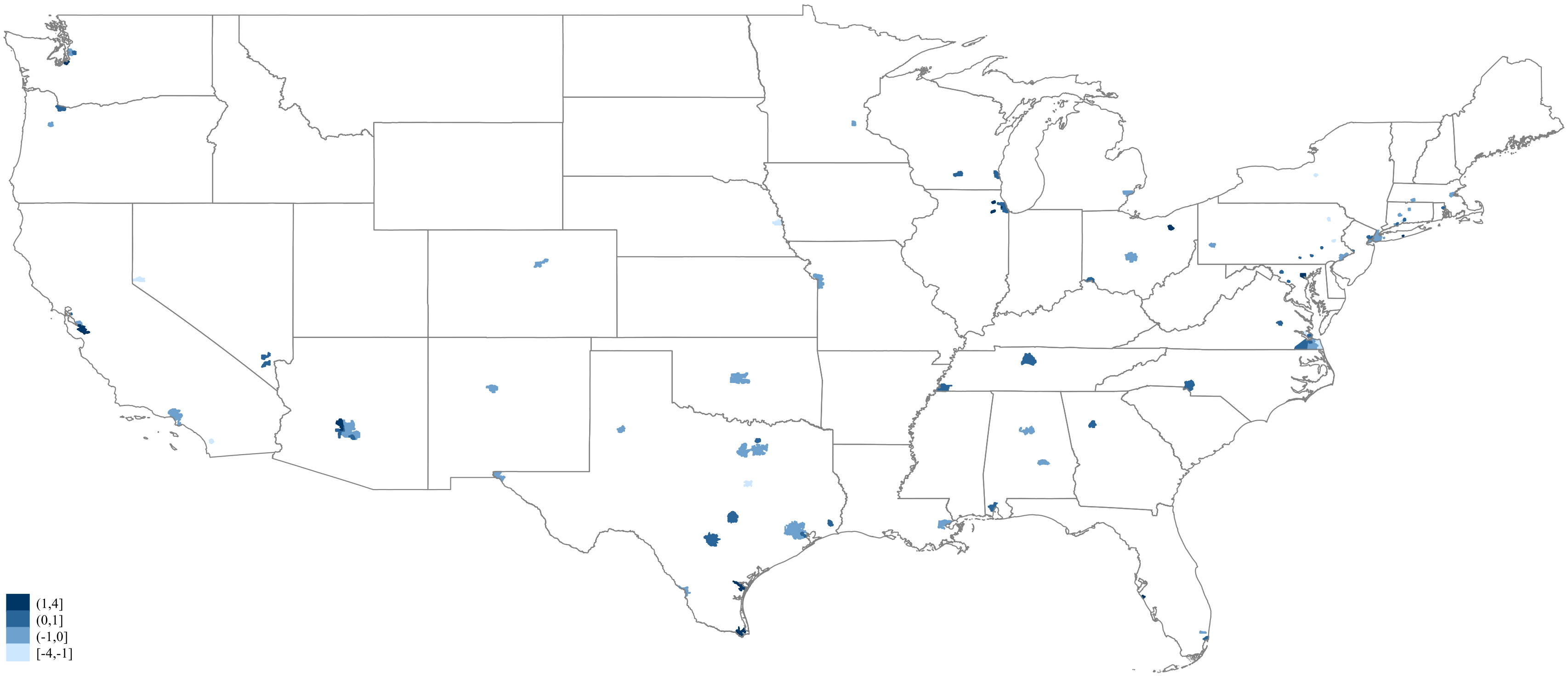
Climate News Sensitivity column reports the averages of bond-level *Climate News Sensitivities* (non-winsorized) at the city level. *Conditional Climate News Sensitivity* column reports the coefficient estimates on city identifiers from an OLS regression of bond-level *Climate News Sensitivities* (non-winsorized) controlling for the bond characteristics listed in Appendix B. Reported in parentheses are the standardized measures computed as a city's *Climate News Sensitivity* minus the mean of cities' *Climate News Sensitivities* divided by the standard deviation of cities' *Climate News Sensitivities*.

City	Climate News Sensitivity	Conditional Climate News Sensitivity	City	Climate News Sensitivity	Conditional Climate News Sensitivity
Birmingham, AL	-0.43 (-0.41)	1.78 (-0.01)	Frederick, MD	0.15 (0.07)	2.11 (0.25)
Mobile, AL	-0.01 (-0.06)	2.04 (0.19)	Rockville, MD	-0.43 (-0.41)	1.82 (0.02)
Montgomery, AL	-0.64 (-0.59)	0.92 (-0.68)	Detroit, MI	1.76 (1.40)	1.60 (-0.15)
Avondale, AZ	0.53 (0.38)	2.47 (0.53)	Minneapolis, MN	-0.43 (-0.41)	1.42 (-0.29)
Chandler, AZ	-0.12 (-0.16)	1.89 (0.08)	Kansas City, MO	-0.69 (-0.63)	1.18 (-0.48)
Gilbert, AZ	-0.72 (-0.65)	1.06 (-0.57)	Charlotte, NC	0.08 (0.01)	1.89 (0.08)
Glendale, AZ	1.19 (0.93)	2.24 (0.35)	Omaha, NE	-1.86 (-1.59)	-0.24 (-1.58)
Mesa, AZ	-0.26 (-0.27)	1.46 (-0.26)	Bayonne, NJ	-0.84 (-0.75)	0.45 (-1.04)
Peoria, AZ	4.83 (3.94)	6.80 (3.90)	Irvington Twp, NJ	-0.94 (-0.83)	1.06 (-0.57)
Phoenix, AZ	-0.24 (-0.25)	1.62 (-0.13)	Jersey City, NJ	1.65 (1.31)	2.69 (0.70)
Scottsdale, AZ	-1.19 (-1.04)	0.86 (-0.73)	Newark, NJ	0.46 (0.32)	1.91 (0.09)
Tempe, AZ	-0.24 (-0.25)	1.78 (-0.01)	Trenton, NJ	0.91 (0.70)	2.56 (0.60)
Berkeley, CA	-0.21 (-0.23)	1.84 (0.04)	Albuquerque, NM	-0.27 (-0.28)	1.22 (-0.44)
Escondido, CA	-3.92 (-3.30)	-3.15 (-3.85)	Carson City, NV	-0.86 (-0.77)	0.51 (-1.00)
Fremont, CA	-1.17 (-1.02)	0.88 (-0.71)	Henderson, NV	0.68 (0.51)	2.60 (0.63)
Los Angeles, CA	-0.30 (-0.30)	1.46 (-0.26)	North Las Vegas, NV	1.64 (1.30)	2.28 (0.38)
San Jose, CA	3.45 (2.80)	5.68 (3.03)	Brookhaven, NY	1.34 (1.05)	3.52 (1.35)
Denver, CO	-1.01 (-0.89)	0.69 (-0.86)	Hempstead Town, NY	-1.24 (-1.08)	0.54 (-0.97)
Bridgeport, CT	-0.76 (-0.69)	0.82 (-0.76)	New York, NY	-0.30 (-0.30)	1.40 (-0.30)
Hamden, CT	1.26 (0.99)	2.93 (0.89)	Syracuse, NY	-1.37 (-1.19)	0.21 (-1.23)
Hartford, CT	0.56 (0.41)	1.50 (-0.23)	Yonkers, NY	0.04 (-0.02)	1.79 (0.00)
New Haven, CT	-1.00 (-0.88)	0.27 (-1.18)	Akron, OH	2.32 (1.86)	3.98 (1.71)
Stratford, CT	1.32 (1.04)	2.33 (0.42)	Cincinnati, OH	-0.87 (-0.78)	2.68 (0.69)
Waterbury, CT	0.17 (0.08)	0.84 (-0.74)	Columbus, OH	-0.97 (-0.86)	0.83 (-0.75)
Miami, FL	0.23 (0.13)	1.82 (0.02)	Oklahoma City, OK	-1.37 (-1.19)	0.60 (-0.93)
Miami Beach, FL	-1.29 (-1.12)	0.95 (-0.65)	Portland, OR	0.56 (0.41)	2.70 (0.71)
Pembroke Pines, FL	-0.85 (-0.76)	1.39 (-0.31)	Salem, OR	-0.49 (-0.46)	1.42 (-0.29)
Sarasota, FL	0.98 (0.75)	3.22 (1.11)	Allentown, PA	-0.46 (-0.44)	-1.35 (-2.45)
Atlanta, GA	0.84 (0.64)	2.71 (0.72)	Lancaster, PA	0.81 (0.61)	2.56 (0.60)
Berwyn, IL	2.44 (1.96)	3.34 (1.21)	Philadelphia, PA	-0.13 (-0.16)	1.51 (-0.22)
Bolingbrook, IL	0.54 (0.39)	3.20 (1.10)	Pittsburgh, PA	-0.07 (-0.11)	1.50 (-0.23)
Chicago, IL	-0.35 (-0.35)	1.90 (0.09)	Reading, PA	0.59 (0.43)	2.12 (0.26)
Schaumburg, IL	0.32 (0.21)	3.35 (1.22)	Scranton, PA	-0.34 (-0.34)	-0.49 (-1.78)
New Orleans, LA	0.02 (-0.04)	1.21 (-0.45)	York, PA	1.32 (1.04)	1.88 (0.07)
Boston, MA	-0.04 (-0.09)	1.73 (-0.05)	Providence, RI	1.20 (0.94)	2.17 (0.30)
Springfield, MA	-0.88 (-0.78)	1.02 (-0.60)	Memphis, TN	0.20 (0.11)	2.00 (0.16)
Baltimore, MD	1.71 (1.36)	3.38 (1.24)	Nashville & Davidson, TN	0.08 (0.01)	1.80 (0.01)

Continued on the next page.

Appendix C continued.

Austin, TX	0.77 (0.58)	2.62 (0.65)	San Antonio, TX	0.62 (0.46)	2.37 (0.45)
Beaumont, TX	0.25 (0.15)	2.27 (0.37)	Waco, TX	-1.84 (-1.58)	0.38 (-1.10)
Brownsville, TX	1.63 (1.29)	3.76 (1.54)	Chesapeake, VA	-1.01 (-0.89)	0.97 (-0.64)
Corpus Christi, TX	1.32 (1.04)	3.58 (1.40)	Hampton, VA	0.33 (0.22)	2.17 (0.30)
Dallas, TX	-0.85 (-0.76)	0.91 (-0.69)	Newport News, VA	-1.21 (-1.06)	0.34 (-1.13)
El Paso, TX	-0.91 (-0.81)	1.09 (-0.55)	Norfolk, VA	0.16 (0.08)	1.37 (-0.33)
Fort Worth, TX	-0.16 (-0.19)	1.61 (-0.14)	Portsmouth, VA	0.95 (0.73)	2.51 (0.56)
Frisco, TX	0.11 (0.03)	1.84 (0.04)	Richmond, VA	0.11 (0.03)	1.88 (0.07)
Garland, TX	-0.58 (-0.54)	1.40 (-0.30)	Suffolk, VA	0.54 (0.39)	2.75 (0.75)
Houston, TX	-0.24 (-0.25)	1.46 (-0.26)	Virginia Beach, VA	-1.93 (-1.65)	-0.08 (-1.46)
Irving, TX	-0.93 (-0.83)	1.21 (-0.45)	Bellevue, WA	0.00 (-0.06)	2.27 (0.37)
Laredo, TX	-0.12 (-0.16)	1.68 (-0.09)	Seattle, WA	-0.33 (-0.33)	1.37 (-0.33)
Lubbock, TX	0.15 (0.07)	1.76 (-0.02)	Tacoma, WA	4.15 (3.38)	5.50 (2.89)
Pasadena, TX	0.35 (0.23)	2.57 (0.61)	Madison, WI	0.19 (0.10)	2.52 (0.57)
Pearland, TX	-1.03 (-0.91)	1.15 (-0.50)	Milwaukee, WI	-0.02 (-0.07)	2.29 (0.39)



Appendix D. The Within-State Variation in Climate News Sensitivities

This map illustrates the standardized *Conditional Climate News Sensitivities* of 104 cities reported in Appendix C. *Conditional Climate News Sensitivities* are the coefficient estimates on city identifiers from an OLS regression of bond-level *Climate News Sensitivities* (non-winsorized) controlling for the bond characteristics listed in Appendix B. For each city, we standardize these *Conditional Climate News Sensitivities* by taking the difference between a city's *Conditional Climate News Sensitivity* and the mean of all cities' *Conditional Climate News Sensitivity* and dividing it by the standard deviation of cities' *Conditional Climate News Sensitivities*. This standardized *Conditional Climate News Sensitivity* has a mean of zero and a standard deviation of one.

Appendix E. Robustness Tests

This table reports the results from the baseline regression of *Yield Spread* (Column (4), Table 2) using alternative specifications. For brevity, this table reports the coefficient estimate on *Climate News Sensitivity*, its statistical significance, the sample size, and R-Squared obtained from alternative regression specifications. Robustness tests (1), (2), and (3) use 6-month, 9-month, and 12-month lags in computing Newey-West adjusted standard errors, respectively, robustness test (4) reports the results from an OLS regression with standard errors clustered at the issuer level, robustness test (5) reports the results controlling for variables that are not winsorized, robustness test (6) controls for *Municipal Bond Market Beta* instead of *Stock Market Beta*, robustness tests (7) and (8) include *Sea Level Rise Exposure* proxy of Hallegatte et al. (2013) and *Climate Damages* estimates of Hsiang et al. (2017) as additional controls, respectively, robustness tests (9) and (10) control for *Amihud* and *Percent of Traded Days*, respectively, as alternative bond liquidity measures, robustness tests (11) and (12) include *Percentage of Adults Believing in Global Warming* and *Percentage Voted Democrat* as additional controls, respectively, the sample in robustness test (13) includes tax-free municipal bonds, robustness test (14) includes *State Income Tax Rate* as an additional control, robustness test (15) includes *State Income Tax Rate* and its interaction with *State Tax Exemption Dummy* as additional controls, the samples in robustness tests (16), (17), and (18) include trades that are executed within the last 10 days of a given month, municipal bonds without credit enhancements, and municipal bonds that are traded more than the median bond in our sample (seven trades in the month prior to the trade date), respectively, the dependent variables in robustness tests (19), (20), and (21) are yield spread over Zero Treasury Curve, Swap Curve, and AAA-Rated Municipal Bond Curve, respectively, the alternative *Climate News Sensitivity* used in robustness test (22) is estimated using the innovations in the negative (i.e., bad) climate news index of Engle et al. (2020), and the samples in robustness tests (23), (24), and (25) include the full sample of 240 cities, cities with a population of at least 100,000, and cities with a population of at least 50,000, respectively. See Appendix A for the details of sample selection process, Appendix B for variable definitions, Table 1 for descriptive statistics on the variables used in the regressions, and Table 2 for the details of the regression model.

Robustness Tests	Coefficient Estimate on Climate News Beta × 100	Sample Size	R-Squared (%)
(1) Newey-West Standard Errors with a 6-Month-Lag	1.40***	43,521	64.49
	(4.10)		
(2) Newey-West Standard Errors with a 9-Month-Lag	1.40***	43,521	64.49
	(3.91)		
(3) Newey-West Standard Errors with a 12-Month-Lag	1.40***	43,521	64.49
	(3.91)		
(4) OLS Regression with Clustered Standard Errors at City Level	1.15**	43,521	59.27
	(2.52)		
(5) Using Variables That Are Not Winsorized	8.99***	43,521	59.57
	(2.88)		
(6) Controlling for Municipal Bond Market Beta	1.86***	43,521	65.53
	(6.29)		
(7) Controlling for Sea Level Rise Exposure	1.55***	26,434	63.77
	(3.59)		
(8) Controlling for Climate Damages	1.40***	43,521	64.62
	(4.69)		
(9) Controlling for Amihud Liquidity Measure	1.50***	34,962	66.09
	(4.19)		
(10) Controlling for Percent of Traded Days	1.40***	43,521	64.53
	(4.74)		

Continued on the next page.

Appendix E continued.

(11) Controlling for Percentage of Adults Believing in Global Warming	1.31*** (4.13)	40,678	65.73
(12) Controlling for Percentage Voted Democrat	1.30*** (4.31)	43,521	64.80
(13) Keeping Bonds without State, Federal, and AMT Taxes	1.08*** (3.24)	33,785	61.80
(14) Controlling for State Income Tax Rate	1.40*** (4.72)	43,521	64.72
(15) Controlling for State Income Tax Rate and its Interaction with State Tax Exemption Dummy	1.45*** (5.02)	43,521	64.95
(16) Keeping Trades Executed During the Last 10 Days of the Month	1.47*** (4.51)	30,276	66.33
(17) Keeping Bonds without Credit Enhancements	1.54*** (4.75)	29,712	66.52
(18) Keeping Liquid Bonds	1.70*** (4.65)	22,445	69.11
(19) Using Yield Spread Over Zero Treasury Curve	1.38*** (5.02)	43,521	63.11
(20) Using Yield Spread Over Swap Curve	1.45*** (4.67)	43,521	67.44
(21) Using Yield Spread Over AAA-Rated Municipal Bond Curve	1.27*** (4.07)	43,521	63.89
(22) Using an Alternative Climate News Sensitivity	4.90** (2.45)	26,305	65.59
(23) Using the Full Sample of 240 Cities	1.41*** (4.61)	48,013	64.44
(24) Using Cities with Populations of at Least 100,000	1.32*** (4.37)	42,244	65.19
(25) Using Cities with Populations of at Least 50,000	1.29*** (4.31)	44,746	64.17

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1. Descriptive Statistics

This table reports the summary statistics for the sample of 45,056 municipal bond-month observations used in the baseline regressions. The municipal bond returns that we use to estimate *Climate News Sensitivity* are available since 2005. As the estimation period requires 60 months of municipal bond returns, *Climate News Sensitivity* is first estimated in January 2010, marking the beginning of the analysis period. The WSJ-based climate change news innovation index of Engle et al. (2020) is available until June 2017, allowing us to estimate *Climate News Sensitivity* by July 2017. This table reports the summary statistics for the sample between January 2010 and July 2017. See Appendix A for the details of sample selection process and Appendix B for variable definitions.

Variables	**N**	**Mean**	**Median**	**Standard Deviation**
The Primary Dependent Variable				
Yield Spread (in Percentages)	45,056	1.43	1.32	1.04
The Independent Variable of Interest				
Climate News Sensitivity	45,056	-0.22	-0.27	1.78
Bond Characteristics				
Issue Amount (in Million USD)	43,789	33.80	22.00	41.30
Time to Maturity (in Years)	45,056	10.13	8.97	6.63
Number of Trades	45,056	10.52	7.00	13.07
Competitive Offering Dummy × 100	45,056	12.28	0.00	32.82
Federal Tax Exemption Dummy × 100	45,056	90.86	100.00	28.82
State Tax Exemption Dummy × 100	45,056	85.56	100.00	35.15
Callable Dummy × 100	45,056	70.94	100.00	45.41
Sinking Fund Dummy × 100	45,056	24.40	0.00	42.95
Credit Enhancement Dummy × 100	45,056	33.60	0.00	47.23
AAA Rated Dummy × 100	45,056	7.64	0.00	26.57
AA Rated Dummy × 100	45,056	72.85	100.00	44.47
A Rated Dummy × 100	45,056	13.69	0.00	34.38
BBB Rated Dummy × 100	45,056	4.59	0.00	20.92
BB Rated Dummy × 100	45,056	0.19	0.00	4.34
B Rated Dummy × 100	45,056	0.03	0.00	1.70
Below B Rated Dummy × 100	45,056	0.45	0.00	6.66
Unrated Dummy × 100	45,056	0.56	0.00	7.49
Beta Estimates				
Stock Market Beta	45,056	0.00	0.00	0.12
Term Spread Beta	45,056	0.26	0.24	0.26
Credit Spread Beta	45,056	0.54	0.45	0.48
City Financials				
Assets (in Billion USD)	45,056	13.90	22.44	13.65
Net Income/Assets × 100	45,045	1.46	0.02	9.57
Cash/Assets × 100	44,776	24.07	21.80	18.40
Liabilities/Assets × 100	45,056	62.54	60.70	29.64

Table 2. Studying the Relationship between Yield Spread and Climate News Sensitivity

This table reports the results from Fama-MacBeth regressions that investigate the cross-sectional relationship between *Yield Spread* and *Climate News Sensitivity*. The sample includes 45,056 monthly municipal bond observations contributed between January 2010 and July 2017. We first run the following regression in each month (t) during our analysis period:

$$Yield\ Spread_i = \alpha + \beta Climate\ News\ Sensitivity_i + X_i^{'}\gamma + \varepsilon_i$$

where $Yield\ Spread_i$ is the difference between yields of municipal bond i and a maturity matched Treasury bond at the end of month t, $Climate\ News\ Sensitivity_i$ is municipal bond i's climate news sensitivity in month t estimated using its monthly returns during the previous 5-year period, and X_i is a vector of control variables. We then report the average of these coefficients estimated monthly during our analysis period (91 months) and compute their statistical significances using Newey-West adjusted standard errors with 3-month lags (Appendix E reports the results with alternative lags). Column (1) includes no control variables, Column (2) controls for *Bond Characteristics*, Column (3) adds *Beta Estimates* to the controls, and Column (4) also includes *City Financials* as additional controls. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. See Appendix A for the details of sample selection process, Appendix B for variable definitions, and Table 1 for descriptive statistics on the variables used in the regressions.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Climate News Sensitivity × 100	2.33***	1.90***	1.52***	1.40***
	(5.18)	(6.30)	(5.58)	(4.74)
Intercept	Yes	Yes	Yes	Yes
Bond Characteristics	No	Yes	Yes	Yes
Beta Estimates	No	No	Yes	Yes
City Financials	No	No	No	Yes
Number of Observations	45,056	43,789	43,789	43,521
R-Squared (%)	0.43	60.78	62.51	64.49

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. Fixed Effects Regressions of Yield Spreads

This table reports the results from fixed effects regressions that investigate the relationship between *Yield Spread* and *Climate News Sensitivity*. Our regression model is as follows:

$$Yield\ Spread_{i,t}=\alpha+\alpha_j+\alpha_{Trade\ Year\text{-}Month}+\beta Climate\ News\ Sensitivity_{i,t}+X_{i,t}^{'}\gamma+\varepsilon_{i,t}$$

where $Yield\ Spread_{i,t}$ is the difference between yields of municipal bond *i* and a maturity matched Treasury bond at the end of month *t*, α_j is the fixed effects for issuer *j*, $\alpha_{Trade\ Year\text{-}Month}$ is the trade year-month fixed effects, $Climate\ News\ Sensitivity_{i,t}$ is municipal bond *i*'s climate news sensitivity in month *t* estimated using its monthly returns during the previous 5-year period, and $X_{i,t}$ is a vector of control variables. Standard errors are clustered at the issuer level. Column (1) excludes the vector of control variables ($X_{i,t}$), Column (2) controls for *Bond Characteristics*, Column (3) adds *Beta Estimates* to the controls, and Column (4) also includes *City Financials* as additional controls. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. See Appendix A for the details of sample selection process, Appendix B for variable definitions, and Table 1 for descriptive statistics on the variables used in the regressions.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Climate News Sensitivity × 100	2.05**	1.42***	0.99**	1.08**
	(2.40)	(3.06)	(2.25)	(2.57)
Intercept	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes
Issuer Fixed Effects	Yes	Yes	Yes	Yes
Bond Characteristics	No	Yes	Yes	Yes
Beta Estimates	No	No	Yes	Yes
City Financials	No	No	No	Yes
Number of Observations	45,056	43,789	43,789	43,521
R-Squared (%)	11.16	49.65	50.27	51.58

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. The Relationship between Yield Spread and Climate News Sensitivity During Alternative Periods

This table reports the results from our baseline Fama-MacBeth regression of *Yield Spread* (Table 2, Column (4)) during different sub-periods. The samples in Columns (1) and (2) include the trades before and after January 2013, respectively, as Goldsmith-Pinkham et al. (2023) show that the physical climate risk has been priced in municipal bond yields since 2013. The samples in Columns (3) and (4) include observations contributed during the below median and above median climate news months, respectively, identified using the WSJ-based climate change news index levels of Engle et al. (2020). The regressions control for *Bond Characteristics*, *Beta Estimates*, and *City Financials*. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. See Appendix A for the details of sample selection process, Appendix B for variable definitions, Table 1 for descriptive statistics on the variables used in the regressions, and Table 2 for the details of the regression model.

Sample:	**Before 2013**	**After 2013**	**Low Climate News Period**	**High Climate News Period**
Variables	**(1)**	**(2)**	**(3)**	**(4)**
Climate News Sensitivity × 100	0.91	1.72***	1.13**	1.67***
	(1.63)	(5.71)	(2.45)	(5.86)
Intercept	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes
Beta Estimates	Yes	Yes	Yes	Yes
City Financials	Yes	Yes	Yes	Yes
Number of Observations	14,060	29,461	20,992	22,012
R-Squared (%)	48.39	75.04	62.04	66.70

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. Variation in the Baseline Results by Bond Maturity and Credit Risk

This table reports the results from regressions that investigate the variation in our baseline finding (Table 2, Column (4)) by the maturity and credit riskiness of municipal bonds. The control variables in Column (1) are the same *Bond Level Controls*, *Beta Estimates*, and *City Financials* as in Column (4) of Table 2, and also include the interaction of *Log(Time to Maturity)* with *Climate News Sensitivity* as an additional control. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Climate News Sensitivity*, *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. Different from the controls in Column (2) of Table 4, Column (2) in this table controls for a continuous *Rating Number* variable instead of rating dummy variables, includes the interaction of *Rating Number* with *Climate News Sensitivity*, and excludes *Credit Enhancement Dummy*, *Beta Estimates*, and *City Financials* as they also proxy for credit risk. The sample in Column (2) excludes unrated bonds. See Appendix A for the details of sample selection process, Appendix B for variable definitions, Table 1 for descriptive statistics on the variables used in the regressions, and Table 2 for the details of the regression model.

Variables	**(1)**	**(2)**
Log(Time to Maturity) × Climate News Sensitivity × 100	0.90*	.
	(1.71)	.
Rating Number × Climate News Sensitivity × 100	.	-0.46**
	.	(-2.12)
Intercept	Yes	Yes
Bond Characteristics	Yes	Yes
Beta Estimates	Yes	No
City Financials	Yes	No
Number of Observations	43,521	43,535
R-Squared (%)	64.66	58.58

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6. The Relationship Between City Characteristics and Climate News Sensitivity

This table reports the results from Fama-MacBeth regressions of *Climate News Sensitivity*. The regression model and the control variables are similar to those in Table 2. The dependent variable in regressions is *Climate News Sensitivity*, the control variables are *Bond Characteristics*, *Beta Estimates*, and *City Financials*, and the standard errors are Newey-West adjusted with 3-month lags. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. Columns (1) through (9) report the coefficient estimates on additional controls that proxy for cities' climate risk characteristics. For ease of interpretation, these additional controls are standardized to have a standard deviation of one. See Appendix A for the sample selection process and Appendix B for variable definitions.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Standardized Sea Level Rise Exposure	1.16	.	.	.	.	.	.	.	.
	(1.57)	.	.	.	.	.	.	.	.
Standardized Climate Damages	.	0.04**	.	.	.	.	.	.	.
	.	(2.04)	.	.	.	.	.	.	.
Log(1+Standardized Number of Flood Instances)	.	.	0.20***	.	.	.	.	.	.
	.	.	(5.31)	.	.	.	.	.	.
Log(1+Standardized Number of Coastal Flood Instances)	.	.	.	0.27***	.	.	.	.	.
	.	.	.	(3.28)	.	.	.	.	.
Log(Standardized Population Density)	.	.	.	.	0.06	.	.	.	.
	.	.	.	.	(1.65)	.	.	.	.
Standardized Percent of Population in Poverty	.	.	.	.	.	0.09***	.	.	.
	.	.	.	.	.	(3.45)	.	.	.
Standardized Percentage of Adults Believing in Global Warming	.	.	.	.	.	.	0.15***	.	.
	.	.	.	.	.	.	(2.81)	.	.
Standardized Percent Voted Democrat	.	.	.	.	.	.	.	0.13**	.
	.	.	.	.	.	.	.	(2.63)	.
Standardized Carbon Intensity of the Economy	.	.	.	.	.	.	.	.	0.08***
	.	.	.	.	.	.	.	.	(2.87)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Beta Estimates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Financials	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	26,434	43,521	40,678	40,678	40,678	40,678	40,678	43,521	40,678
R-Squared (%)	14.96	15.02	14.74	14.80	14.73	15.10	15.05	15.37	15.04

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7. The Influence of Climate News Sensitivity on Offering Yield Spreads

This table reports the results from OLS regressions that investigate the relation between *Offering Yield Spread* and *Climate News Sensitivity*. The sample includes 18,973 new general obligation municipal bonds issued between 2010 and 2017 by 102 of 104 cities in our baseline sample. As the new bond issuances are unbalanced in each month, we run an OLS regression instead of monthly Fama-MacBeth regressions. Our regression equation is as follows:

$$Offering\ Yield\ Spread_i = \alpha + \alpha_{Issue\ Year\text{-}Month} + \beta Average\ Climate\ News\ Sensitivity_j + X'_{i,t}\gamma + \varepsilon_i$$

where *Offering Yield Spread*$_i$ is the difference between the offering yield of municipal bond *i* and the yield on a maturity matched Treasury bond on the issue date (t), $\alpha_{Issue\ Year\text{-}Month}$ is the issue year-month fixed effects, *Average Climate News Sensitivity*$_j$ is the average of climate news sensitivities on issuer *j*'s bonds, and $X_{i,t}$ is a vector of control variables. Standard errors are clustered at the issuer level. Column (1) excludes the vector of control variables ($X_{i,t}$), Column (2) controls for *Bond Characteristics*, Column (3) adds *Beta Estimates* to the controls, and Column (4) also includes *City Financials* as additional controls. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Average Stock Market Beta*, *Average Term Spread Beta*, and *Average Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. See Appendix A for the details of sample selection process, Appendix B for variable definitions, and Table 1 for descriptive statistics on the variables used in the regressions.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Climate News Sensitivity × 100	7.64***	2.55**	2.79*	2.40*
	(3.11)	(2.03)	(1.89)	(1.73)
Intercept	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes
Bond Characteristics	No	Yes	Yes	Yes
Beta Estimates	No	No	Yes	Yes
City Financials	No	No	No	Yes
Number of Observations	18,973	18,973	18,973	18,642
R-Squared (%)	19.22	71.51	71.68	72.16

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8. Testing the Hedging Demand Mechanism

This table reports the results from regressions that investigate whether the investor demand for hedging climate risks influence our findings. We assume that municipal bonds that are exempt from state taxes issued in states with income taxes appeal to local investors. These municipal bonds (Local Investor Base Sample) would face less demand for hedging climate risk when compared to the remaining municipal bonds (Global Investor Base Sample). Columns (1) and (2) report the results of our baseline regression (Column (4), Table 2) for the Global Investor Base and Local Investor Base subsamples, respectively. The control variables are the same *Bond Level Controls*, *Beta Estimates*, and *City Financials* as in Column (4) of Table 2. *Bond Characteristics* include *Log(Issue Amount)*, *Log(Time to Maturity)*, *Log(1+Number of Trades)*, *Competitive Offering Dummy*, *Federal Tax Exemption Dummy*, *State Tax Exemption Dummy*, *Callable Dummy*, *Sinking Fund Dummy*, *Credit Enhancement Dummy*, *AAA Rated Dummy*, *AA Rated Dummy*, *A Rated Dummy*, *BBB Rated Dummy*, *BB Rated Dummy*, *B Rated Dummy*, and *Below B Rated Dummy*, *Beta Estimates* include *Climate News Sensitivity*, *Stock Market Beta*, *Term Spread Beta*, and *Credit Spread Beta*, and *City Financials* include *Log(Assets)*, *Net Income/Assets*, *Cash/Assets*, and *Liabilities/Assets*. See Appendix A for the details of sample selection process, Appendix B for variable definitions, Table 1 for descriptive statistics on the variables used in the regressions, and Table 2 for the details of the regression model.

Sample:	**Global Investor Base**	**Local Investor Base**
Variables	**(1)**	**(2)**
Climate News Sensitivity × 100	1.56***	1.44***
	(3.06)	(4.18)
Intercept	Yes	Yes
Bond Characteristics	Yes	Yes
Beta Estimates	Yes	Yes
City Financials	Yes	Yes
Number of Observations	12,033	31,488
R-Squared (%)	73.50	65.36

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

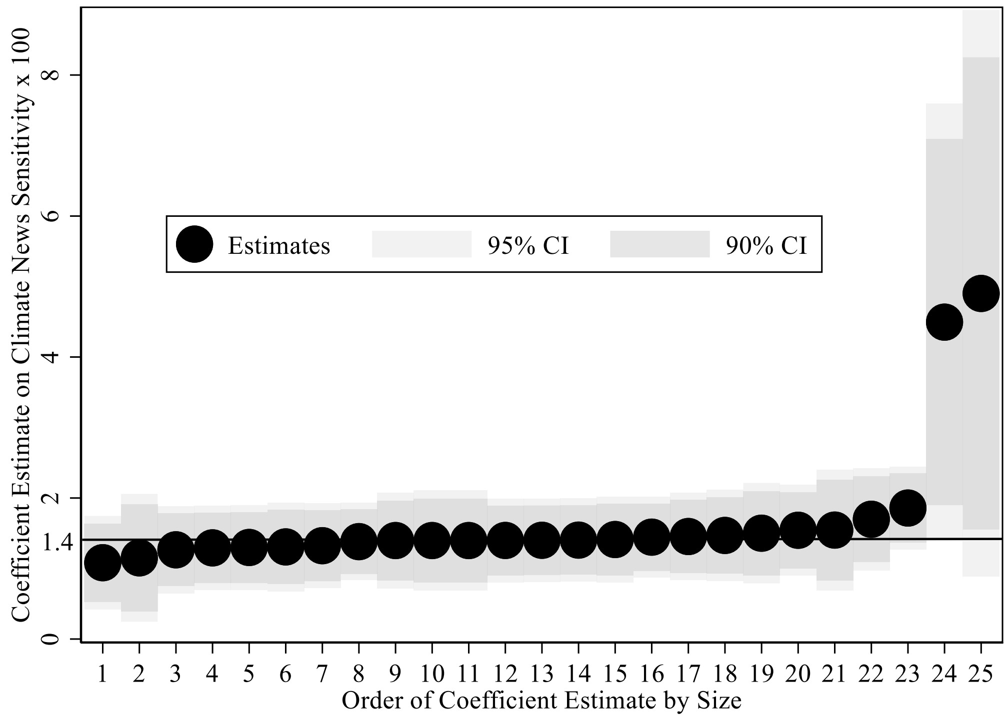


Figure 1. Robustness Tests

This figure plots the coefficient estimates on *Climate News Sensitivity*—along with their 90% and 95% confidence intervals—from the baseline regression of *Yield Spread* (Column (4), Table 2) using alternative specifications. The vertical axis reports the coefficient estimates on *Climate News Sensitivity* multiplied by 100, and the horizontal axis reports the order of these coefficient estimates based on their sizes. The coefficient estimates, arranged in ascending order of their magnitudes, are from the following tests: (1) studying tax-free municipal bonds; (2) estimating an OLS regression with standard errors clustered at the issuer level; (3) using yield spread over AAA-Rated Municipal Bond Curve as the dependent variable; (4) studying cities with a population of at least 50,000; (5) controlling for *Percentage Voted Democrat*; (6) controlling for *Percentage of Adults Believing in Global Warming*; (7) studying cities with a population of at least 100,000; (8) using yield spread over Zero Treasury Curve as the dependent variable; (9) using 9-month lags in computing Newey-West adjusted standard errors; (10) using 6-month lags in computing Newey-West adjusted standard errors; (11) using 12-month lags in computing Newey-West adjusted standard errors; (12) controlling for *Climate Damage* estimates of Hsiang et al. (2017); (13) controlling for *State Income Tax Rate*; (14) controlling for *Percent of Traded Days;* (15) studying the full sample of 240 cities; (16) controlling for *State Income Tax Rate* and its interaction with *State Tax Exemption Dummy*; (17) using yield spread over Swap Curve as the dependent variable; (18) studying trades that are executed within the last 10 days of a given month; (19) controlling for *Amihud* liquidity measure; (20) studying municipal bonds without credit enhancements; (21) controlling for *Sea Level Rise Exposure* proxy of Hallegatte et al. (2013); (22) studying municipal bonds that are traded more than the median bond in our sample (seven trades in the month prior to the trade date); (23) controlling for *Municipal Bond Market Beta* instead of *Stock Market Beta*; (24) controlling for variables that are not winsorized (the coefficient on *Climate News Sensitivity* from this regression is halved for visual comparability with the rest of the estimates); (25) using the innovations in the negative (i.e., bad) climate news index of Engle et al. (2020) when constructing *Climate News Sensitivity*. For each of these regressions, Appendix E reports the coefficient estimate on *Climate News Sensitivity*, its statistical significance, the sample size, and the model fit in a table format.