Crops, Drops, and Bonds: The Impact of Water Risk on U.S. Municipal Bond Yields*

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Abstract We study the relation between water availability, water demand, and U.S. municipal bond yields to explore how water stress affects local costs of debt. We define 'water stress' as the imbalance between water availability and water demand within a county. We focus on agriculture-dependent counties in the U.S. and use satellite data to obtain their water availability and needs. By combining these datasets, we construct a novel county-level water risk measure that allows us to estimate which counties are under physical water stress. We find a significantly positive relation between our water risk measure and municipal bond yields while controlling for traditional municipal bond determinants. Initial evidence indicates that this effect is stronger for highly indebted counties. In sum, our findings suggest that lowering water stress may lower the cost of debt for local U.S. governments.

Keywords: Water stress, droughts, soil water content, crop production, U.S. municipal bond yields, spatial finance

JEL classification: .

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"...soil water is the most necessary resource on the planet. It stops us from starving. It is vital. And yet it is politically and economically invisible. It is ignored. Like sleeping children in the back seat of a car, we are ignorant of what is carrying us forward."

— Virtual Water: Tackling the Threat to Our Planet's Most Precious Resource, by Allan, 2011

1. Introduction

Freshwater, a finite resource, is critical for various industries, ecosystems, and basic human welfare (Dai, 2011). Its availability, however, is under increasing stress due to a constant increase in global demand, driven by population growth and dietary changes (Boretti and Rosa, 2019). Water is becoming an increasingly scarce commodity as projections suggest that by 2050, nearly half of the global population will reside in water-stressed regions (United Nations World Water Assessment Programme, 2018). The term 'water stress' in this paper refers to situations where the available water supply fails to meet the regional water demand. Given the exacerbating effect of climate change on water stress (Iordache, Nechita, Voica, Pluháček, and Schug, 2022), it is essential to understand whether water stress will have an effect on local economies and financial markets.

In this paper, we address this question by assessing whether there is a relation between water stress and U.S. municipal bond yields. We use municipal bonds to analyze this relation since the local risks of water stress might directly impact municipalities' cash flows backing these bonds. The municipal bond market, therefore, reflects the general local economic conditions (Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2022). In addition, we focus on municipal bonds of counties that are dependent on the agricultural sector. We believe the relation between water stress and economic outcomes will be most pronounced in these regions as 72 percent of global freshwater withdrawals go to agriculture and droughts affect farmers directly (Mekonnen and Hoekstra, 2016). Droughts are important to our study because they are a clear indicator of reduced water availability, a key component in our water stress definition. Previous literature on droughts has found that they can impact public health, the natural environment, and the economy (NCEI, 2023; Freire-González, Decker, and Hall; 2017; Wilhite, Svoboda, and Hayes, 2007). Furthermore, droughts drive local and national governments to increase public expenditures and subsidies (Freire-González et al., 2017), and these additional costs and the reduced business activities in the agricultural sector can significantly impact a local government's creditworthiness. Therefore, we hypothesize that water stress is related to increased municipal bond yields.

Our paper contributes to the emerging spatial finance literature, which combines geospatial data with financial information (Caldecott, McCarten, Christiaen, and Hickey, 2022). In our analysis, we use soil moisture observations to account for water availability. We use soil water content from the Planetary Variables dataset provided by Planet. Planet offers comprehensive geospatial data using its satellites and public constellations (Planet, 2018). A key advantage of using soil water content is that it estimates the direct water availability to plants. Soil moisture incorporates water loss through evaporation and runoff following precipitation, thus providing a complete understanding of water availability. In addition, for farming areas, the soil moisture observations also include the water from irrigation as the soil moisture values measure the amount of water in the soil, combining the water from precipitation and water added by farmers. The ability to include runoff and irrigation water sets our soil moisture measurement apart from the commonly used Palmer Drought Severity Index (PSDI), which relies on precipitation and temperature data. Our unique dataset enables us to capture the spatiotemporal variations in soil moisture, which is crucial to understanding water availability and calculating drought conditions.

We construct monthly drought categories for each county to capture these drought conditions. We follow the approach of the USDM (2023) and calculate drought categories ranging from normal (0) to exceptional drought (5). A drought becomes critical when the water demand, e.g., from households and the agriculture sector, exceeds a region's water supply due to the drought. Therefore, we construct a novel water risk measure (WRM) by combining drought categories (indicating water availability) with a county's commodity production acres (indicating water demand) to measure a county's water stress. Following the approach of Rodziewicz, Dice, and Cowley, 2023, we construct the WRM by multiplying the share in agricultural acres with our monthly drought categories to obtain the county-specific monthly WRM.

We use the municipal bond yields from the Municipal Securities Rulemaking Board (MSRB) as our dependent variable. As municipal bonds are not frequently traded and following the insights in Auh, Choi, Deryugina, and Park (2022), we construct a monthly panel of volume-weighted yields at a county level from July 2012 through December 2019. We use a panel regression model to assess the relation between water risk and municipal bond yields. We present our results using two distinct specifications, county fixed effects and state fixed effects. To control for seasonality, we always include month fixed effects. As the effects of water risk on municipal bond yields may not be immediate, we incorporate three distinct lags for the WRM in our analysis: a 1-month lag, a 3-month lag, and a maximum 6-month lag, the latter reflecting the approximate duration of the longest crop growing season.

In the main regression, we find a significant positive relation between municipal bond yields and the WRM. Specifically, for the county fixed effects model, an increase of one standard deviation in water risk is associated with a yield increase of 1.56 basis points for the 3-month lagged WRM and 1.82 basis points for the 6-month lagged WRM. For the state fixed effect estimator, the results are economically stronger. A standard deviation increase in the WRM is associated with a rise in yield ranging from 2.34 to 2.86 basis points for the 3-month and 6-month lagged WRM, respectively. While our findings are on a monthly basis, they broadly align with findings from Acharya, Johnson, Sundaresan, and Tomunen, 2022, who reported a five bps increase per annum in yield spreads associated with a one standard deviation increase in heat stress exposure. This comparison suggests a consistency in the relation between environmental stress factors and U.S. municipal bond yields, though it is important to acknowledge the differences in time frames and specific types of stress examined. Our findings suggest an important relation between water risk and local costs of debt. In addition, these results seem to indicate that the market prices water risk in the months after a drought.

We continue our analyses to better understand this relation. We argue that droughts impact local governments via increased costs or a loss in tax revenue via increased public expenditures and subsidies (Freire-González et al., 2017). High debt levels typically increase municipal bond yields; an increase in water risk, and therefore, an increase in costs, might increase the yield for these highly indebted counties more. Our findings show initial evidence that an increase in the

1-month lagged WRM for highly indebted counties is associated with a higher yield increase than for lower indebted counties. Nevertheless, since the results are not statistically significant for the 3- and 6-month lag WRM models, we must exert caution in interpreting the 1-month lag WRM model results. We continue our analyses by estimating whether the relation between municipal bond yields and the WRM is stronger for counties more dependent on local revenue streams than federal or state revenue streams, as we argue that reduced business activities in the agricultural sector can significantly impact a local government's income. However, we find little evidence that the WRM has an increased effect on counties that are more dependent on local revenue.

We further examine whether the relation between the municipal bond yields and the WRM is stronger for shorter-term bonds. The average growing season of crops is six months (D'Agostino and Schlenker, 2016). This period is important for the agricultural business and, consequently, for the local economy. In the event of a drought or increased water risk, short-term municipal bond investors may be particularly concerned about the impact on agriculture and the spillover effect on the local economy and the creditworthiness of the local government (Freire-González et al., 2017). In contrast, long-term investors might view the same drought as an incident, expecting that over a longer horizon, the local economy could recover or adapt. Our hypothesis differs from previous climate finance research, which finds that environmental shocks tend to impact long-term bonds more. The findings of our analysis are not statistically significant. Thus, we cannot draw meaningful conclusions on whether short-term or long-term bonds are more affected by water risk.

In the U.S., crop yields or revenue can be insured via the Federal Crop Insurance Program (FCIP). Farmers producing row crops are well insured against potential losses due to weather events. Approximately 82 percent of eligible acres among producers of row crops are insured (USDA, 2023a), compared to roughly 3 percent of the livestock farms (Rodziewicz et al., 2023). Specialty crop farmers also have low insurance rates. Rodziewicz et al. (2023) find a strong relation between drought-related farmer's losses and producing noninsured crops. Hence, we estimate whether the relation between municipal bond yields and the WRM is stronger for counties that produce low-insured crops (livestock and specialty crops). Our results, however, find little evidence that an increase in the WRM impacts counties producing low-insured crops more than counties producing high-insured products like row crops.

The USDA Economic Research Service publishes County Typology Codes that classify the U.S. counties based on their economic dependence. The economic dependence of a county can be classified into farming, mining, manufacturing, Federal/State government, and recreation. We argue that the relation between municipal bond yields and the WRM is stronger for counties economically dependent on farming income. The results, however, cannot find evidence that counties economically dependent on agriculture have a stronger relation between the WRM and municipal bond yields than other counties.

In summary, our findings offer initial evidence of a potential positive relation between the WRM and U.S. municipal bond yields; however, we approach our conclusions with caution due to certain limitations in our empirical analysis. Notably, the forward-looking bias inherent in our WRM, stemming from how we construct the drought categories, and our current methodology's inability to establish causality are concerns. Nevertheless, the statistically significant relation we identify provides a foundation for ongoing analysis to further establish the robustness of and assess the dynamics of the relation between water stress and U.S. municipal bond yields.

Our study contributes to the existing body of climate finance literature of, among others, Acharya et al. (2022), Goldsmith-Pinkham et al. (2022), Albert, Bustos, and Ponticelli (2023), Rizzi (2022) and Hong, Li, and Xu (2019). For example, Hong et al. (2019) find that stock markets are not efficiently pricing drought risk, consistent with the underreaction of food prices to climate risks. In addition, Acharya et al. (2022) established a significant positive relation between local heat exposure and municipal bond spreads. However, their water stress measure, from Moody's Four Twenty Seven, using geographical exposures to climate change did not yield comparable results. They argue that their results on local heat exposure arise from expected energy cost increases and lower productivity. We differ from Acharya et al. (2022) in three ways: first, we introduce a novel water risk measure that integrates soil moisture data—a key indicator of water availability crucial for agricultural viability—with crop acres data, which reflects water demand. This combination allows us to estimate a county's physical water stress. Secondly, we focus our analysis on agriculture-dependent counties, arguing that the correlation between water stress and economic outcomes will be most pronounced in these regions. Thirdly, we look for a direct relation between water stress and municipal bonds.

As climate change is making water stress a pressing issue, actions like improving water conservation, using water more efficiently, and adopting sustainable water management are important. Our research provides preliminary evidence that can potentially support local governments in pushing for these changes. For investors, our findings may help investors make better-informed investment decisions. However, more than that, we hope our initial findings will encourage efforts to use water more wisely.

2. Background and Motivation

2.1. Water stress and droughts

Droughts can impact various sectors, including corporations, farms, households, and the environment (Wilhite, 1992). However, the actual impact of a drought is contingent upon its effects on regional water availability. Specifically, a drought becomes critical when it leads to a deficiency in water supply relative to the demand within a region, such as a county. This mismatch between supply and demand is often called 'water scarcity' or 'water stress.' Due to the subtle differences and ongoing debates regarding these terms among various institutions, this paper will consistently use the term 'water stress' to refer to situations where the available water supply fails to meet the regional demand.

Our research focuses on drought conditions as they signal lowered water availability, an essential element in our definition of water stress. Wilhite and Glantz (1985) define four types of droughts; meteorological, agricultural, hydrological, and socioeconomic. Meteorological drought is a period of below-normal precipitation, often accompanied by high temperatures (Dai, 2011 and Mishra and Singh, 2010).[1] Agricultural drought is defined as soil water deficiency, a direct measure of green

[1] One of the best-known indicators of meteorological drought is the Palmer drought severity index (PSDI) (Wilhite and Glantz, 1985).

water, during the crucial stages of the crops' growing season (Heim Jr, 2002).[2] A hydrological drought develops slowly and is characterized by depleted stored water, such as lakes and rivers (Dai, 2011). A socioeconomic drought occurs when there is insufficient water due to weather-related shortfall, leading to a water shortage for the economic needs of a region.

In this paper, we use soil moisture data from Planet Labs PBC (2023) to measure drought conditions. The benefit of using soil moisture is that it incorporates water loss through evaporation and runoff following precipitation, thus providing a complete understanding of water availability. In addition, for farming areas, this method naturally also includes the water from irrigation as the soil moisture values measure the amount of water in the soil, combining the water from rain and the water added by people. Furthermore, surface soil moisture is vital for the health of crops and livestock (Heim Jr, 2002). It is essential that when we analyze droughts, we employ relative measures (Wilhite and Glantz, 1985); a standalone soil moisture value provides little insight into the soil's relative dryness or wetness. Its value and drought conditions depend on the typical soil moisture for that specific time and location.

We introduce a novel measure of water stress for U.S. counties focusing on the agricultural sector. Agriculture is a significant water user, accounting for approximately 72% of global freshwater demand, making it crucial to consider in any assessment of water stress (Mekonnen and Hoekstra, 2016). Our measure of water stress focuses on water demand and availability. We adopt the framework of Rodziewicz et al. (2023), considering the proportion of agricultural land allocated as a proxy of regional water demand. We use relative soil moisture measures to calculate water availability. Our approach combines agricultural land use with relative soil moisture conditions to measure water stress for U.S. counties, with a particular emphasis on their agricultural production.

2.2. Droughts, food production, and local economies

As previously discussed, droughts can have far-reaching effects, impacting sectors and services such as agriculture, labor, tourism, water quality, ecosystems, and public safety due to forest fires, and increasing inequality caused by unequal distribution of relief funds (Wilhite, 1992, Albert et al.,

[2] Water is categorized into blue (surface and groundwater) and green (rainwater absorbed by soil and vegetation).

2023 and Albert et al., 2023). In the United States, the average annual damages due to droughts are estimated between 6 and 8 billion dollars (Dai, 2011). While droughts impose a broad range of economic burdens nationwide, one of the most direct impacts is felt in the agricultural sector. For instance, Lesk, Rowhani, and Ramankutty (2016) examined the global impact of extreme weather events on cereal production from 1964 to 2007, finding that droughts and extreme heat significantly reduced national cereal production by 9–10 percent. In addition, Rodziewicz and Dice (2020) find evidence of drought-related farmer's losses, depending on the crop type.

The ripple effects of reduced crop yields due to insufficient soil moisture levels (Liu et al., 2016, Kuwayama, Thompson, Bernknopf, Zaitchik, and Vail, 2019) can extend beyond the farm, influencing local economies as reduced agricultural productivity can lower tax revenues for local governments (Rodziewicz and Dice, 2020). These lower revenues can affect public services and infrastructure development, impacting the local economy. In addition, Wilhite and Glantz (1985) explains that municipalities can be affected by the economic loss to industries dependent on agricultural production. Drought mitigation measures, water transport, or transfer costs can also reduce the municipalities' cash flows backing the municipal bonds. These additional costs and potential local economic loss can raise the local government risk perceived by bond investors, increasing municipal bond yields. Given the evidence from previous literature, we argue that water stress can negatively impact the economy of counties that heavily depend on producing and exporting agricultural products and, thus, indirectly can increase municipal bond yields for these counties.

Furthermore, considering that droughts can significantly affect counties' income and revenue streams, we argue that the relation between drought and municipal bonds is stronger for counties with a high debt-to-tax ratio, meaning those with substantial debt. Typically, high local debt levels increase yields on municipal bonds as the pricing of default risk is high in municipal bond markets and accounts for about 75% of the spreads Schwert (2017). In these financially strained counties, the potential rise in costs due to droughts could lead investors to view the already considerable debt as an even higher default risk, consequently driving up the yields on these municipal bonds even further. In addition, counties in the U.S. can depend more on local revenue streams or federal revenue streams. Given the domino effect of a drought, we suggest that the relation between water stress and municipal bond yields is stronger for counties more dependent on local revenue streams. A decreased tax revenue from industries dependent on agricultural production may lower a county's local revenue which is an important determinant of the ability to pay debt. Counties that depend more on federal or state revenue streams can be less affected by this risk.

Additionally, we posit that the relation between water stress and municipal bond yields can differ for different maturity bonds. Crop growing season can differ per crop as soybeans take, on average, three months to grow, and grapes take six months to harvest. Nevertheless, on average, the crop growing season is approximately six months from seed to harvest (D'Agostino and Schlenker, 2016).[3] This period is important for the agricultural business and, consequently, for the local economy. In the event of a drought or increased water stress, short-term municipal bond investors may be particularly concerned about the impact on agriculture, the spillover effect on the local economy, and the creditworthiness of the local government (Freire-González et al., 2017). Long-term investors might view a drought or increased water stress as an incident, arguing that the economy will recover or adapt. Therefore, we argue that the relation between municipal bond yields and water stress is stronger for short-term bonds than for long-term maturity bond yields. This argumentation is in line with the cash flow news channel, which is characterized by short-term impact rather than the discount channel, which impacts municipal bond yields more in the long term.

2.3. Agriculture, crop insurance, and farm income

The U.S. produces several agricultural commodity types categorized as row crops, specialty crops, livestock, and forage crops. Row crops comprise, among others, corn, soybeans, wheat, and borgum. Specialty crops include fresh or dried fruits, tree nuts, vegetables, beans, and horticulture nursery crops. Livestock (also called 'Rangeland' in this paper) includes grasslands and shrubland used for cattle to graze on. Forage crops are crops such as hay and alfalfa that are eaten additionally by grazing livestock.

In the U.S., crop yields or revenue can be insured via the Federal Crop Insurance Program

[3] Our data includes summer and winter crops and livestock, so pinpointing the overarching growing season is impossible.

(FCIP). In 2021, the total agricultural land in the U.S. was 895,300 million acres, and about 50 percent (444,437 million acres) of it was insured (USDA, 2021 and USDA, 2023a). Roughly 50 percent of this insured land were acres dedicated to producing row crops, 40 percent to forage crops, and 10 percent to specialty crops. Most FCIP liabilities are attributable to row crops, with 70 percent of insured liability in 2021 (USDA, 2023a). Specialty, livestock, and forage crops represent 18, 8, and 3 percent of the insured liabilities. The remaining one percent of insured liability is for other crops.

Farmers producing row crops are well insured against potential losses due to weather events. The average annual FCIP participation from 2000 to 2021 covered 82 percent of eligible acres among producers of row crops (USDA, 2023a). Livestock insurance only gained traction in the last couple of years. Glauber (2022) explains that livestock insurance coverage was minimal due to maxima on expenditures limiting producer subsidies. The livestock insurance has grown significantly after these caps were lifted in 2018. In 2021, the total insured liabilities soared to $14 billion, marking an increase of approximately 2,800 percent from a mere $512 million recorded in 2018 (Glauber, 2022). As of 2021, roughly 3 percent of the livestock is insured (Rodziewicz et al., 2023).

For specialty crops, the insurance levels are different across various crops. Farmers of specialty crops can rely on FCIP insurance or the Farm Service Agency's (FSA) Noninsured Crop Disaster Assistance Program (NAP). The latter is essential for farmers in counties where information about crop growth is insufficient to be able to use FCIP insurance. Skorbiansky et al. (2022) state that the value of specialty crops insured by FCIP has grown 75 percent from 2011 to 2020. California, Florida, and Washington - states leading predominantly in fruit and vegetable production - and Montana and North Dakota - states excelling in dry beans and peas production - hold the highest number of insurance policies (Skorbiansky et al., 2022).

Rodziewicz et al. (2023) find a strong relation between drought-related farmer's losses and producing noninsured crops. As these lowered farmers' income can indirectly indicate a lower tax revenue for counties, we argue that the relation between water stress and municipal bond yields is stronger for counties that produce crops with lower insurance coverage, such as specialty crops and livestock.

2.4. Agriculture contribution

The U.S. Department of Agriculture, Economic Research Service (2023) publishes yearly U.S. farm sector income and wealth statistics. From their publications, we can observe that from 2014-2022, on average, livestock agriculture (meat plus dairy sales) contributed approximately 34% of the total U.S. commodity cash receipts. Row crops contributed, on average, roughly 28% of receipts—forage crops, 2%, and specialty crops, 12%. These numbers indicate that livestock farming and producing row crops contribute most to U.S. commodity sales.

Production agriculture, agriculture, forestry, fishing, and hunting, contributed $206.6 billion to the U.S. economy in 2021, accounting for 0.9% of the total U.S. GDP (White, 2023). It was particularly significant in nonmetro counties, generating about 4.8% of the 2021 GDP in these counties. White (2023) also finds that counties with the most significant proportion of GDP from production agriculture typically have smaller populations. However, this trend contrasts with certain larger counties that, despite their size, have a substantial agricultural output. These counties often produce specialty crops, which significantly contribute to their local GDP. For instance, Madera County in California, notable for its production of almonds and pistachios—categorized as specialty crops—saw agriculture constituting 23.6% of its GDP in 2021 (White, 2023).

In addition to understanding the agriculture contribution to GDP, the USDA Economic Research Service publishes County Typology Codes that classify U.S. counties based on their economic dependence. The economic dependence of a county can be classified into farming, mining, manufacturing, Federal/State government, and recreation. We argue that the relation between municipal bond yields and water stress is stronger for counties economically dependent on farming income.

3. Data

3.1. Soil Water Content

Our primary variable of interest is soil water content. In this study, the terms 'soil water content' and 'soil moisture' are used interchangeably to refer to the same measure of water present in the soil.

Soil water content is part of the Planetary Variables data from Planet Labs PBC (2023). Planet Labs PBC (2023) utilizes remote sensing techniques and data from its satellites and from public constellations. The data from the Planetary Variables is collected on a daily basis. We obtained daily soil moisture observations from July 2012 until December 2022. The soil water content is ideal for assessing droughts as the soil moisture content quantifies the water available to plants. To illustrate, the soil water content includes evaporation, runoff after precipitation, and irrigation water and, therefore, gives a more complete picture of water availability than solely relying on precipitation data. For example, Planet Labs PBC (2023) assists farmers in 17 countries with soil water content data to defend against drought's impact and predict crop yields (van der Schalie, 2022).

The soil water content that Planet Labs PBC (2023) produces estimates the amount of water in the top layer of the soil and is expressed in m^3/m^3. For example, a value of 0.2 means that in a volume of 1 m^3, 0.2 m^3 is water, and 0.8 m^3 consists of other materials (e.g., sand, clay, biomass). Our soil water content represents how much water is present at a depth of 4.5-7.5 centimeters (Andrew et al., 2022). Figure 1 shows an example of a high-resolution image of the soil water content retrieved by the Soil Moisture Active Passive satellite.

As previously stated, when assessing droughts, one should employ relative measures (Wilhite and Glantz, 1985); a standalone soil moisture value provides little insight into the soil's relative dryness or wetness. Its value and drought conditions depend on the typical soil moisture for that specific time and location. Therefore, we construct a soil moisture anomaly index. Following several other papers, Dai 2011, D'Agostino and Schlenker 2016, Wilhite and Glantz 1985 and Jenkins, Dobson, Decker, and Hall 2021, we construct an index by comparing current soil water content levels to the average levels for the same time of the year over a historical period locally. We follow the approach of USDM (2023), which provides information on how the U.S. Drought Monitor (USDM) identifies areas in drought and labels them by intensity. USDM (2023) express the current soil water content as a percentile based on historical data and consider an area to be in a normal state if the soil water content is in the 31st percentile or higher. The other classifications include abnormally dry (21^{st} to 30.99^{th}), moderate (11^{st} to 20.99^{th}), severe (6^{th} to 10.99^{th}), extreme (3^{th}

to 5.99^{th}), or exceptional drought (0^{th} to 2.99^{th}). This measure allows us to analyze the impact of the different types of drought on local economies.

To create the drought categories, we first calculate each county's long-term average soil water content per month.

$$LT\,Avg\,Soil_{i,m} = \frac{1}{\sum_{y \in Y} Obs_{i,m,y}} \sum_{y \in Y} \sum_{o=1}^{Obs_{i,m,y}} S_{i,d_o,y},$$

where, $LT\,Avg\,Soil_{i,m}$ is the long-term average soil water content for county i for month m over all years, 2012-2022. $Obs_{i,m,y}$ is the number of soil moisture observations for month m in year y in county i, $S_{i,d_o,y}$ represents the soil water content of country i the observed day d_o of month m in year y. d_o is the specific day for which an observation exists in month m in year y.

Then, we calculate each county's average soil water content for the months in a particular year.

$$\text{AvgSoil}_{i,m,y} = \frac{1}{Obs_{i,m,y}} \sum_{o=1}^{Obs_{i,m,y}} S_{i,d_o,y},$$

where $Avg_{i,m,y}$ represents the average soil water content for country i, in month m in year y. $Obs_{i,m,y}$ is the number of soil water content observations for month m in year y in county i. $S_{i,d_o,y}$ represents the soil water content of country i the observed day d_o of month m in year y. d_o is the specific day for which an observation exists in month m in year y.

The drought category, denoted as $DroughtCategory_{i,m,y}$, is a numerical value based on the percentile deviation from a county's long-term average for a specific month m ($LTAvgSoil_{i,m}$). When the average soil water content ($AvgSoil_{i,m,y}$) of a particular month m, year y for county i is between the percentiles as discussed above, the $DroughtCategory_{i,m,y}$ is 0 when the average soil water content is considered normal, 1 when its abnormally dry, 2 moderate, 3 severe, 4 extreme, and 5 when there is an exceptional drought.

Figure 2 reports the proportion of counties that experienced a particular type of drought. At the end of 2017, almost 45 percent of counties experienced mild dryness or drought. Exceptional droughts, based on our soil moisture data, are uncommon and rarely happen as shown in Figure 2.

Ideally, the long-term average soil moisture, denoted as $LT\,Avg\,Soil_{i,m}$, for each county i in month m, would be calculated using out-of-sample data. This approach would allow us to define drought categories by comparing this out-of-sample average and the in-sample average soil moisture, $Avg_{i,m,y}$. However, we aim to maximize the number of observations used in the analyses. Therefore, both $LT\,Avg\,Soil_{i,m}$ and $Avg_{i,m,y}$ are calculated in-sample. Consequently, our methodology might underestimate the occurrence of exceptional droughts since our reference points are derived from the same period as the data being analyzed. Moreover, our reliance on in-sample data makes our categorization of drought conditions inherently 'future' biased. This bias means our drought categories would not be directly tradeable for real-time decision-making, as they incorporate 'future' soil moisture information.

3.2. Crop data

As previously discussed, we develop a novel measure of water stress that combines soil moisture data (indicating water availability) with commodity production acres (indicating water demand), following Rodziewicz et al. (2023). The commodity production acres are available via CropScape. CropScape is a tool made public by the USDA National Agricultural Statistics Service, which includes cropland cover in the continental U.S. (Boryan, Yang, Mueller, and Craig, 2011 and Han, Yang, Di, and Mueller, 2012). Using satellite imagery, the Cropland Data Layer (CDL) Program estimates the number of acres dedicated to, among other categories, agriculture, forest, developed open spaces, and aquaculture at a county-year level. (Boryan et al., 2011).

The CDL program provides information on various commodity products—for example, barley, spring and winter wheat, tomatoes, alfalfa, watermelons, and grapes. We follow Rodziewicz et al. (2023) and the USDA with their definition of rangeland (also called 'Livestock' in this paper) and use the categories grass pasture, shrubland, and clover/wildflowers to measure the acres of rangeland in a county. This wide range of information about planted crop acres allows us to analyze the relation between different crop categories, drought, and municipal bonds.

Figure 3 shows the predominant crop category for each county in 2021 based on the crop acreage. The crop categories include *Row crops*, *Forage crops*, *Rangeland*, and *Specialty crops*.[4] Details regarding the categorization of crops can be found in Appendix A.

We also use the data from CropScape to indicate which counties are producing more insured agricultural products and which are producing lower insured products. We define counties where *Rangeland* or *Specialty crops* are the dominant crop category as lower-insured counties.

3.3. Water Risk Measure

Combining the drought categories and crop acres data allows us to finally construct a novel water risk measure that estimates a county's physical water stress. The drought categories based on our soil water content data will enable us to understand the relative local water availability. The crop acres data allows us to infer water demand.

First, we calculate the total agricultural land of a county as a percentage of the total acres in that county.

$$SAL_{i,y} = \frac{\sum_{c=1}^{4} CropArea_{i,y,c}}{TotalArea_{i,y}},$$

where $SAL_{i,y}$ is the share of agricultural land in county i in year y. $CropArea_{i,y,c}$ is the acres in county i in year y for crop type c (*Row Crops*, *Forage Crops*, *Rangeland*, and *Specialty Crops*). $TotalArea_{i,y}$ is the total acres in county i in year y.

Second, we multiply the drought category for county i, in month m and year y with the share of agricultural land.

$$WRM_{i,m,y} = DroughtCategory_{i,m,y} * SAL_{i,y},$$

where $WRM_{i,m,y}$ is the Water Risk Measure for county i in month m in year y. The $DroughtCategory_{i,m,y}$ ranges from 0 - normal soil water conditions - to 5 - exceptional drought conditions. $SAL_{i,y}$ is the share of agricultural land in county i in year y. In the following sections, the terms 'water risk' and 'water stress' are used interchangeably. Both terms refer to the WRM for each county.

By construction, the WRM is 0 when there is no measurable drought in the county at a specific

[4] For instance, if a county has 1,000 acres dedicated to *Row Crops*, 500 acres to *Rangeland*, and 20 acres each to the other two categories, then *Row Crops* would be represented as the dominant crop category for that county in Figure 3.

time. Also, by design, the WRM increases in importance when the agricultural acres in a county are high, automatically increasing the water stress of a drought for that county.

3.4. Municipal bonds

The municipal bonds data is from the Municipal Securities Rulemaking Board (MSRB). This dataset includes all municipal bond transactions from 2005 to 2020. We utilize information on the bond yield, coupon rate, time to maturity, issue size, and trade volume. As in Gao, Lee, and Murphy (2019), only customer buy transactions have been incorporated to mitigate time series fluctuations resulting from the bid-ask bounce. Similar to Schwert (2017), the analysis is focused solely on fixed-coupon and tax-exempt bonds that traded at least ten times.[5] This latter selection criteria assures a level of uniformity and a minimum level of liquidity.

Also, we remove transactions that occur after a bond's advance refunding date, as after this date, the bond can be considered risk-free (Chalmers, 1998). We also remove trades in the first three months after issuance and the final year before maturity due to the noisy nature of these periods (Green, Hollifield, and Schürhoff, 2007 and Schultz, 2012). Callable bonds have also been excluded to eliminate complications arising from embedded options.

As in Green, Li, and Schürhoff (2010), we remove clear data errors such as observations with missing information on the coupon and maturity across all records, observations with coupons exceeding 20% or recorded maturities greater than 100 years, and transactions where the price falls below 50% of face value. Lastly, we remove trades recorded after the maturity date.

We supplement the MSRB data with hand-collected bond attributes from Bloomberg. This additional information includes issuer name, county of issuance, offering yield, sources of funds, general obligation (GO) indicator, use of proceeds, credit rating, insurance status, and pre-refunding status and timing. When information regarding the county associated with a bond is missing, efforts have been made to collect this data manually.

By combining the transaction data from MSRB with Bloomberg's supplementary information, a monthly panel of volume-weighted yields has been constructed at the county level. In other words,

[5] We eliminate federally taxable bonds and bonds eligible for alternative minimum tax (AMT).

we have one observation per county i, in month m in year y.

3.5. County Economic Data

The economic and population data at the county level are collected from the U.S. Bureau of Economic Analysis (BEA), the U.S. Census Bureau, and the U.S. Bureau of Labor Statistics (BLS). Specifically, we utilize county-level population, personal income, and unemployment rate from 2010 to 2020. We enhance this information with the counties' financial characteristics. This dataset includes local government debt, cash and securities, and tax revenue. We measure the local revenue ratio based on the composition of general revenue sources for local governments. These sources include intergovernmental (IG) revenue from federal and state governments and local revenue. In addition, we construct the debt-to-tax ratio to evaluate whether the municipal bond yields of highly indebted counties have a stronger relation to droughts than for lower indebted counties.

To analyze whether the county's dependence on agriculture may result in a stronger relation between droughts and municipal bond yields, we include the County Typology Codes from the USDA Economic Research Service. These Typology Codes classify the U.S. counties based on their economic dependence. The dependence can be classified into farming, mining, manufacturing, Federal/State government, and recreation. This classification allows us to assess which counties rely more heavily on agriculture than others.

Details about the number of housing units and home prices are recovered from the U.S. Census (U.S. Census Bureau, 2000), the American Community Survey (U.S. Census Bureau, 2016), and Zillow's Home Value Index (ZHVI).

3.6. Descriptive statistics

Table 1 presents the summary statistics (number of observations, mean and median, standard deviation, minimum and maximum values) for the variables in our dataset. The sample includes 2,110 counties from July 2012 to December 2019.

Our yield variable's minimum (0.00%) and maximum value (96.10%) show a large difference.

This result does not indicate outliers. The high average yields are concentrated within counties with high average yields. For example, we observe the average yield in our period of 48.65% for the Mississippi county in Missouri. The large difference between average years to maturity (2 years - 68.49 years) has a similar explanation as the average yield. High maturities are typical in some counties. The average years to maturity of municipal bonds in the county of Athens, Ohio, steadily increased from 12 years in 2013 to 68 years in 2017, with an average of 27.71 years.

The Share of agriculture acres variable shows we have counties in our dataset with low agriculture acres (e.g., Monroe County, Florida) and large shares of agricultural land (e.g., Loving County, Texas). These shares of agriculture acres impact the WRM, which ranges from a minimum value of 0 to 4.09.

To enhance the interpretability of the coefficients in our regression analyses, we have scaled down the variables Population, Local income, and Trading volume by dividing each by a million. This adjustment addresses the large magnitudes of these variables and allows for a more straightforward interpretation of the resulting coefficients.

The variables Debt-to-tax ratio and Local revenue ratio are transformed into quintiles per the method described in Auh et al. (2022). For the Debt-to-tax ratio, a quintile value of 1 corresponds to counties with the highest debt (highly indebted), while a quintile value of 5 indicates counties with the lowest level of debt. Conversely, for the Local revenue ratio, a quintile value of 1 denotes counties most dependent on local revenues, whereas a value of 5 indicates counties that primarily rely on federal revenue streams.

We use the County Typology Codes from the USDA Economic Research Service and create the *Agriculture dependence dummy* that equals 1 when the county is economically dependent on farming. On average, not many counties depend economically on farming; this is visible via the low mean of the Agriculture dependence dummy.

The *Agricultural insurance dummy* equals 1 for low-insured counties. We define counties where *Rangeland* or *Specialty crops* are the dominant crop category as these lower-insured counties.[6]

[6] A county may produce both *Rangeland* and *Row crops*. As *Row crops* are well insured, we do not want our results influenced and therefore define counties with a row crop-rangeland ratio of >50% as high-insured.

Approximately 54 % of our counties produce low-insured crops.

4. Empirical Approach

4.1. Main model

To assess the relation between water stress and municipal bond yields, we estimate the following panel model:

$$Y_{i,m,y} = \beta_0 + \beta_1 WRM_{i,m-l,y} + \lambda' X_{i,m,y} + \varepsilon_{i,t} \tag{1}$$

where $WRM_{i,m-l,y}$ is the Water Risk Measure (WRM) for county i, in month $m-l$ of year y and assesses the water stress of the county. Here, l denotes the lag in months applied to the WRM, as the effects of water stress on municipal bond yields may not be immediate. Given the varying growing seasons for different crops, the impact of the WRM on municipal bond yields could have a delay. To accommodate this, we incorporate three distinct lags in our analysis: a 1-month lag, a 3-month lag, and a maximum 6-month lag, the latter reflecting the approximate duration of the longest crop growing season.[7] This approach allows us to capture the potential delayed relation between water stress and municipal bond yields.

The vector of control variables, X, includes bond-level characteristics averaged at the county level (coupon rate, years to maturity, and trading volume) and county characteristics (personal income, employment, housing price index growth, population, local revenue ratio, and debt-to-tax ratio). We use a one-period lag in the model for the county characteristics of personal income, unemployment rate, house price index growth, and population.

In our analysis, we present the outcomes using two distinct specifications. The initial specification integrates county fixed effects, thereby accounting for all unobserved, time-invariant influences that might impact the yield of municipal bonds within each county. However, as our dataset comprises a single volume-weighted average yield observation for each county, this method effectively

[7]By construction the number of observations used in the three specifications will decrease when the WRM lag increases. This reduction occurs because the longer lag periods require more preceding data points for each observation, reducing the total number of observations that meet this criterion.

includes 'bond'-fixed effects. This rigorous specification demands many degrees of freedom, making it a comprehensive yet resource-intensive approach. In contrast, our second specification draws inspiration from the methodology used by Bolton and Kacperczyk (2023), who include analyses that incorporate firm- and industry-fixed effects, offering a nuanced examination of the data. We opt for state fixed effects to distinguish potential outcome differences. To control for seasonality, we include month fixed effects, as these specifically target to capture seasonality.

4.2. Additional Analyses

To test our argument that highly indebted counties may show a stronger water risk-yield relation, we replace the Debt-to-tax ratio and include a dummy that equals 1 when the debt-to-tax ratio is either one or two to Eq. 1. Furthermore, we include an interaction term between the WRM and the dummy to Eq. 1. We expect a positive coefficient on the interaction term, as that means water risk is associated with a higher increase in yield for highly indebted counties.

Similar to the previous analyses, we test our hypothesis on local revenue dependence similarly. We replace the Local revenue ratio with a dummy that equals 1 when the Local revenue ratio is either one or two. In addition, we include an interaction term between the WRM and this Local revenue dummy to Eq. 1. We expect a positive coefficient for the interaction term, as this indicates that water risk is associated with a higher increase in yield for counties more dependent on local revenue streams.

Furthermore, to estimate the relation between different maturity municipal bond yields and water stress, we replace the Years to maturity variable with a dummy that equals 1 when the Years to maturity value is 5 years or lower.[8] In addition, we include the interaction between the dummy and the WRM in Eq. 1. We hypothesize a positive coefficient for this interaction term, indicating that the impact of water stress on municipal bond yields is stronger for short-term bonds.

To estimate the relation between water risk and municipal bond yields conditional on crop insurance, we include the Agriculture insurance dummy, which is 1 when a county relies most on

[8]Preferably, we would have included the Years to maturity variable and the interaction between the WRM and the Years to maturity variable to Eq. 1. However, including both the interaction and the WRM variable led to severe multicollinearity issues in the model.

producing livestock or specialty crops, and the interaction term between the WRM and dummy to Eq. 1. We expect a positive interaction coefficient as we hypothesize that the relation between water risk and municipal bond yields is stronger for counties dependent on producing low-insured agricultural products.

In addition, we estimate the relation between water risk and municipal bond yields in light of the county's agricultural contribution. We add the Agriculture dependence dummy (1 when the county economically relies on farming) and the interaction term between the dummy and the WRM to Eq. 1. The interaction indicates the impact of water risk on counties dependent on agricultural revenue streams. Consistent with our hypothesis, we expect the coefficient to be positive. The Agriculture dependence dummy does not change for a county over the time period; therefore, in the county fixed effects specifications, the dummy gets omitted by construction.

5. Results

5.1. Water risk and municipal bond yields

Table 3 shows the results of the relation between the municipal bond yield and the WRM by estimating Eq. (1). Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively.

The results of Table 3 indicate that the municipal bond yield and the WRM are positively related. Similar to our hypothesis, we find a significant positive relation for the county and state fixed effect specifications for the three- and six-month lagged WRM. The coefficient of the 1-month lagged WRM is also positive, but it is not statistically significant. In the county fixed effects model, an increase of one standard deviation increase in water risk is associated with a yield increase of 0.0156% (1.56 basis points) for the 3-month lagged WRM and 0.0182% (1.82 basis points) for the 6-month lagged WRM. For the state fixed effect estimator, the results are economically stronger. A standard deviation increase in the WRM is associated with a rise in yield ranging from 0.0234%

to 0.0286% (equivalent to 2.34 to 2.86 basis points) for the 3-month and 6-month lagged WRM, respectively.[9]

While the changes in basis points appear modest, their financial implications can impact counties or states, especially when considering large bond issuances. In 2023, the total U.S. municipal bond issuance reached 380.5 billion dollars, with general obligation (GO) municipal bonds accounting for 126.8 billion dollars (*US Municipal Bonds Statistics*, 2023 and Howard, 2023). Distributing this figure across 47 states of our sample and twelve months yields an average issuance of approximately 224.8 million dollars per state. At this scale, even a seemingly slight increase of 0.0156% translates to an additional 35,000 dollars in interest payments per state, while an increase of 0.0286% equates to about 65,000 dollars per state. For a state with an economy the size of Louisiana's—valued at 231,262 dollars million in 2022—these increments represent a substantial 0.015% and 0.028% increase in interest payments, respectively (Bureau of Economic Analysis, 2023). These figures show how even minor shifts in basis points can affect the financial burden of interest payments for states.

In addition, while our findings are on a monthly basis, they broadly align with findings from Acharya et al., 2022, who reported a 5 bps increase per annum in yield spreads associated with a one standard deviation increase in heat stress exposure. This comparison suggests a consistency in the relation between environmental stress factors and U.S. municipal bond yields, though it is important to acknowledge the differences in time frames and specific types of stress examined.

We observe a difference in the economic significance of the WRM variable when comparing the county fixed effect to the state fixed effect specifications. The state fixed effects mitigate omitted variable bias that uniformly affects all counties within a state. Examples include statewide policies, environmental conditions, economic climates, and tax regulation. On the other hand, the county fixed effect specification is more stringent, capturing all time-invariant variations specific to each county, a level of detail the state fixed effects does not reach. This difference in the scope of variation each model captures could explain the observed higher economic significance in the state fixed effect specification.

[9] While the total number of observations varies with each lagged WRM, the standard deviation of the WRM consistently remains 0.26 across all lags.

The control variables show logical relations. Higher maturity bonds are associated with higher yields, and an increase in the unemployment rate is also associated with an increase in yield. Meanwhile, an increase in house prices is associated with a decrease in average yield in a county, similar to an increase in trading volume.

5.2. Debt, local revenue streams, and maturity

In this subsection, we analyze whether the relation between the municipal bond yield and the WRM is stronger for counties that are highly indebted or rely more on local revenue streams. Furthermore, we analyze whether the relation is stronger for shorter-maturity municipal bonds.

Table 4 shows the results of the analyses that estimate whether the relation between the municipal bond yield and WRM is stronger for highly indebted counties. We argue that droughts impact local governments via increased costs or a loss in tax revenue. Typically, high debt levels increase municipal bond yields; a high WRM might increase the yield further. The results of Table 4 do not give conclusive evidence of a stronger relation between the municipal bond yield and the WRM for highly indebted counties. The interaction term between the WRM and Debt-to-tax dummy (indicating high-debt counties) is only statistically significant for the 1-month WRM lag, albeit for both county- and state fixed effect specifications. The positive coefficient suggests that an increase in water risk is associated with an additional increase in yield. More specifically, for highly indebted counties, a standard deviation increase in WRM is associated with a yield rise of 1.5 bps in the county fixed model and 2.7 bps in the state fixed model.[10] To illustrate, if the current yield of a municipal bond is equal to the average of our sample, 2.55, the standard deviation increase in WRM is associated with a 0.5% [0.015/2.55] or 1.1% increase in yield for that bond. However, for the 1-month lagged WRM model, both the WRM coefficient and the dummy variable show no statistical significance in either specification, with the lagged WRM coefficient becoming slightly negative but minimal in magnitude.

Furthermore, we find a positive coefficient for the interaction term in both specifications and for the 3- and 6-month lag WRM model. Indicating that even though the coefficient is not statistically

[10] The standard deviation of the Debt-to-tax dummy is 0.46. Hence, $0.46 * 0.26 * 0.125 = 0.01495$.

significant, the sign of the coefficient remains in line with our hypothesis. We again find a significant positive relation for the county- and state fixed effect specifications for the three- and six-month lagged WRM. All else equal, for the county fixed effect specification, a standard deviation increase in the 3-month lagged WRM and 6-month lagged WRM is associated with one bps and 1.6 bps increase in municipal bond yield, respectively. For the state fixed effects specification, a standard deviation increase in the 3- and 6-month lagged WRM is associated with a yield increase of 1.2 bps and 1.9 bps, respectively. Overall, the result of Table 4 provides some evidence for our debt hypothesis. Nevertheless, since the results are not statistically significant for the 3- and 6-month lag WRM models, we must exert caution in interpreting the results of the 1-month lag WRM model. Nonetheless, the results do support the consistently positive correlation previously observed between municipal bond yields and the WRM.

We continue our analyses by estimating whether the relation between municipal bond yields and the WRM is stronger for counties more dependent on local revenue streams. A drought can have a negative ripple effect throughout the local community and economy; counties that rely more on local revenue streams could, therefore, be more impacted than counties relying on federal or state income. Table 5 shows the results of our hypothesis. The main variable of interest is the interaction term between the WRM and the Local revenue dummy. Except for the 1-month lagged WRM model with the state fixed effect specification, all interaction coefficients are positive. These results seem to indicate that the relation between the WRM is stronger for counties dependent on local revenue streams. However, the interaction term is not statistically significant in any of the specifications. Again, we find a significant positive relation between the municipal bond yield and WRM. We again find the economically strongest relations for the 6-month lagged WRM. In the county fixed effect specification, a standard deviation increase in the lagged WRM is associated with a 1.4 bps increase in yield. For the state fixed effect specification, a standard deviation increase is associated with a 2.4 bps increase in yield. Overall, the results of Table 5 do not provide evidence for our local revenue hypothesis.

We now examine whether the relation between the municipal bond yields and the WRM is stronger for shorter-term bonds. In Table 6, shows the results of including the Maturity dummy (equal 1 for a maturity lower than 5) and the interaction term between the Maturity dummy and the WRM. We hypothesize that diminished crop yields due to drought will be quickly visible, and therefore, the relation between the municipal bond yield and the WRM is stronger for shorter-maturity bonds. The variable of interest is the interaction term. In contrast to our hypothesis, the coefficient for the interaction term is negative in both specifications and for all lagged WRM models. These results suggest that an increase in the WRM is associated with a decrease for short-term municipal bond yields. These results align with general climate finance findings, which find that environmental shocks impact long-term bonds more. Nevertheless, in our models, although negative, the interaction term is not statistically significant. The 3- and 6-month lagged WRM variables remain statistically significant and positive for the two fixed effect specifications. In summary, while Table 6 does not provide evidence of our initial hypothesis regarding bond maturity, it presents limited evidence that suggests a relation inverse to our supposition.

5.3. Crop insurance and agricultural contribution

In the following subsection, we focus more on the agricultural side of the research. We estimate the relation between municipal bond yields and the WRM conditional on whether counties produce low-insured crops. In addition, we analyze whether the relation between municipal bond yields and the WRM is stronger for counties more dependent on farming income.

Table 7 shows the results of the regressions that estimate whether the relation between the municipal bond yield and WRM is stronger for counties producing low-insured crops. Previous literature finds that a drought negatively impacts the farmer's income, which produces low-insured crops. These reduced incomes may impact counties through lower tax income. Therefore, we argue that the interaction term between the WRM and the Insurance dummy (low-insured crop production) is positive, indicating a stronger relation between municipal bond yields and WRM for counties that produce more low-insured crops. Table 7 portrays a positive interaction term for the 1- and 3-month lagged WRM for the county fixed effects specification. However, the interaction terms are not statistically significant. In the other specifications and lagged WRM models, the interaction term is negative, although minimal in magnitude, and also not statistically significant. Consistently, the 6-month lagged WRM demonstrates the most pronounced economic impact. Specifically, within the county fixed effect framework, a one standard deviation increase in the lagged WRM is associated with an increase of 2.0 bps in yield. Similarly, under the state fixed effect specification, this same increase in WRM is associated with a yield increase of 3.1 bps. Overall, Table 7 does not provide any evidence of a stronger relation between the municipal bond yield and the WRM for counties producing more low-insured crops.

Proceeding with our analysis, we examine whether the relation between the municipal bond yields and the WRM is stronger for counties dependent on agriculture. Table 8 shows the results of including the Agriculture dependence dummy and the interaction term between the dummy and the WRM. In line with your hypothesis, we expect a positive interaction coefficient. We find a positive coefficient for the interaction term for the 1- and 3-month lagged WRM in the county fixed effects specification. These coefficients indicate a stronger relation between the municipal bond yield and the WRM for agriculture-dependent counties. However, neither interaction term is statistically significant. Also, the other specifications do not portray a statistically significant interaction term. However, we do find statistically significant positive coefficients for the 3- and 6-month lagged WRM for both specifications.

6. Conclusion

Our research contributes to the growing body of climate finance and spatial finance research. Our primary purpose is to better understand the relation between water stress and local government debt. Therefore, we study the relation between municipal bond yields and our Water risk measure (WRM). Our WRM measures water stress by combining data on water availability and water demand for counties in the United States. Our findings can be summarized as follows. First, we find a significantly positive relation between municipal bond yield and the WRM. Our most strict model, county fixed effects, suggests that an increase of one standard deviation of water risk is associated with a 1.56 to 1.82 basis points increase in yield. For the state fixed effect estimator, the results are economically stronger. A standard deviation increase in the WRM is associated with an increase in yield ranging from 2.34 to 2.86 basis points. We interpret our conclusions with caution due to certain limitations in our empirical analysis. Nevertheless, the statistically significant relation we identified provides a foundation for ongoing analysis to further establish the robustness of and assess the dynamics of the relation between water stress and U.S. municipal bond yields. Second, we find some evidence that the relation between municipal bond yields and the WRM is stronger for highly indebted counties. However, we find a statistically significant result in only two models. Therefore, we must exert caution in interpreting this result. Third, we analyze whether bond characteristics, specific agricultural products, or agricultural economic dependence impact the relation between municipal bond yields and the WRM. Our results do not find conclusive evidence for this.

Our study finds an initial relation between an increase in water risk and higher municipal bond yields. In a world where climate change is making water scarcity a growing concern, actions like improving water conservation, using water more efficiently, and adopting sustainable water management are important. Our research provides preliminary evidence that may support local governments in pushing for these crucial changes. For investors, our findings may help investors make better-informed investment decisions. But more than that, we hope our findings will encourage efforts to use water more wisely.

A. Different categories of crops

In the paper we define *Row Crops*, *Forage Crops*, *Rangeland*, and *Specialty Crops* as follows.

A.1. Row Crops

Row crops are crops that are replanted every year and get their name from the 'rows' in which they are planted (USDA, 2023c). The top eight crops in the U.S. barley, corn, cotton, oats, rice, sorghum, soybeans, and wheat (USDA, 2023c). To measure the total acres of row crops we include:

1. Winter Wheat
2. Spring Wheat
3. DurumWheat
4. Buckwheat
5. Soybeans
6. Corn
7. Sorghum
8. Cotton
9. Rice
10. Oats
11. Barley

A.2. Forage Crops

Forage crops are crops and grasses that are planted for feeding livestock. We include the following crops to calculate the total forage crop acres:

1. Alfalfa
2. Sod Grass
3. Other Hay Non Alfalfa
4. Rye
5. Millet
6. Triticale

A.3. Rangeland

We follow Rodziewicz et al. (2023) and the USDA's definition of rangeland and use the categories grass pasture, shrubland, and clover/wildflowers to measure the acres of rangeland in a county.

A.4. Specialty crops

Specialty crops are considered "fruits and tree nuts, vegetables, culinary herbs and spices, medicinal plants, as well as nursery, floriculture, and horticulture crops" (USDA, 2023b). The crops included in our specialty crop measure:

1. Almonds
2. Grapes
3. Apples
4. Apricots
5. Avocados
6. Nectarines
7. Olives
8. Blueberries
9. Citrus
10. Pears
11. Pecans
12. Cherries
13. Pistachios
14. Plums
15. Prunes
16. Cranberries
17. Pomegranates
18. Strawberries
19. Walnuts
20. Caneberries
21. Asparagus
22. Mustard
23. Dry Beans
24. Peas
25. Broccoli
26. Onions
27. Cabbage
28. Carrots
29. Cauliflower
30. Peppers
31. Celery
32. Potatoes
33. Pumpkins
34. ChickPeas
35. Radishes
36. Turnips
37. Cucumbers
38. Eggplants
39. Squash
40. SweetCorn
41. Garlic
42. SweetPotatoes
43. Tomatoes
44. Lentils
45. Lettuce
46. Watermelons
47. HoneydewMelons
48. Cantaloupes
49. Mint
50. Herbs
51. Hops
52. Greens

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Figure 1 High-resolution soil water content image

Figure 1 shows an example of a high-resolution image of the soil water content retrieved by Planet Labs PBC using data from the Soil Moisture Active Passive (SMAP) satellite.

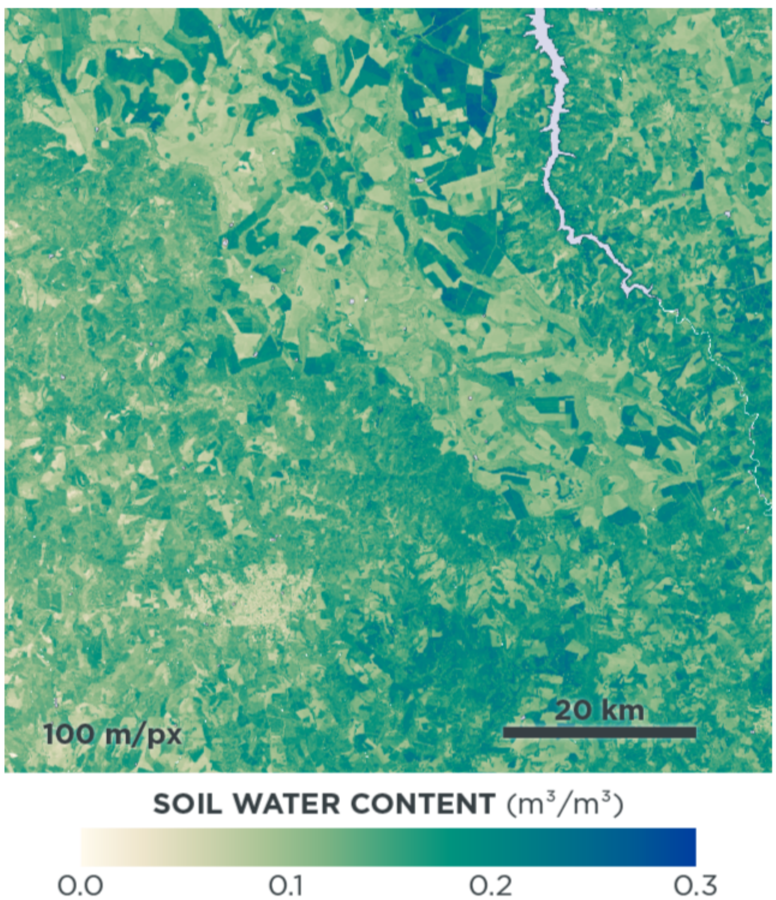

Figure 2 Counties per drought category over time

Figure 2 displays the number of counties, as a percentage of total counties in the dataset, that experienced a particular drought category at a point in time. To measure the drought categories we use the soil water content from Planet (2018). We calculate the average soil water content for county i for month m over all years, 2012-2022. The drought category is calculated as the percentile deviation from a county's long-term average for a specific month. When the soil water content of a particular month m, year y for county x is between the percentiles 21 to 30.99, 11 to 20.99, 6 to 10.99, 3 to 5.99, or 0 to 2.99. The area is considered to be in an abnormally dry, moderate, severe, extreme, or exceptional drought, respectively. The data is scaled to show the percentage of total counties (3,102) that are in a particular drought category.

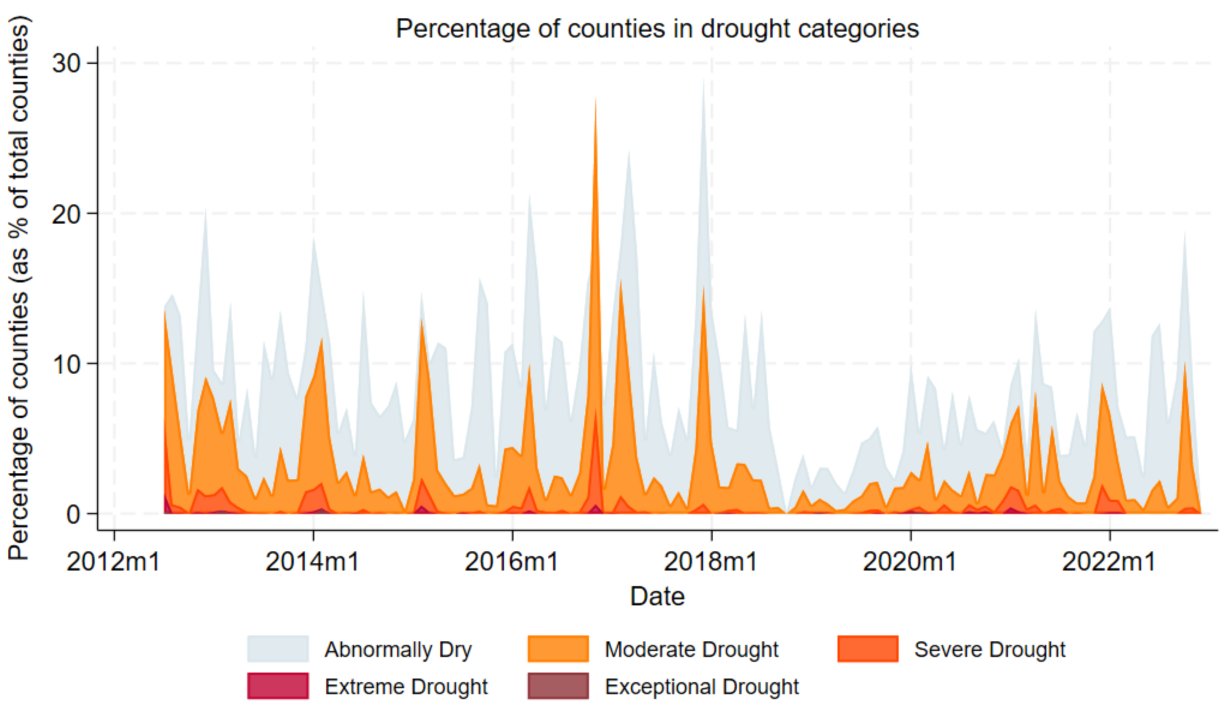

Figure 3 Top crop category per county

Figure 3 showcases the predominant crop category for each county in 2021 based on the acreage dedicated to that crop. Specifically, the depicted crop category for a county is determined by the maximum acreage among the four categories: *Row Crops*, *Forage Crops*, *Rangeland*, and *Specialty Crops*. For instance, if a county has 1,000 acres dedicated to *Row Crops*, 500 acres to *Rangeland*, and 20 acres each to the other two categories, then *Row Crops* would be represented as the dominant crop category for that county in Figure 3. Counties colored in white indicate a lack of data. Further details regarding the categorization of crops can be found in Appendix A

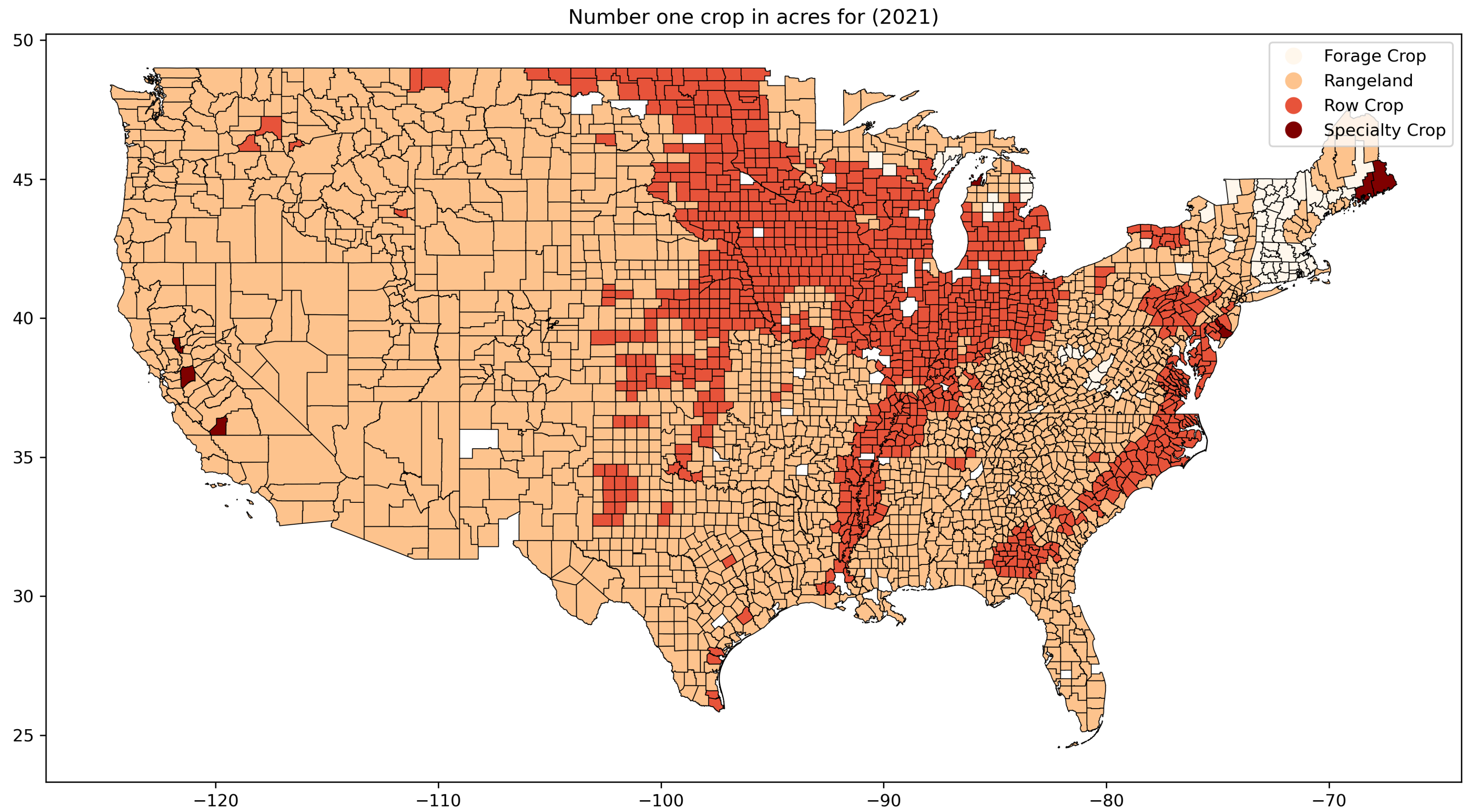

Table 1 Descriptive statistics

This table presents the summary statistics (the number of observations, mean, standard deviation, minimum and maximum values) of the variables used in our research. The *Drought category* is calculated as the percentile deviation from a county's long-term average for a specific month m (See Section 3.3.1: $LTAvgSoil_{i,m}$). When the average soil water content (See Section 3.3.1: $AvgSoil_{i,m,y}$) of a particular month m, year y for county i is between the percentiles 21 to 30.99, 11 to 20.99, 6 to 10.99, 3 to 5.99, or 0 to 2.99. The area is considered to be normal (0), in an abnormally dry (1), moderate, severe, extreme, or exceptional (5) drought. *Water Risk Measure* indicates physical water stress. It is the interaction between the share of agricultural land in county i and the *Drought category*. The *Share of agriculture land* is the sum of the acres dedicated to row crops, forage crops, specialty crops, and range land divided by the total acres of the county obtained from CropScape. The *Yield* is the volume-weighted average yield of all municipal bonds traded in month m in year y in county i. The *Coupon rate*, *Years to maturity* and *Trading volume* control for the volume-weighted average coupon rate, maturity, and trading volume of the bonds traded in month m in year y in county i. *Population*, *Personal income*, and *Unemployment rate* are county-specific determinants that represent the economic health of a county. Where *Population* and *Personal income* are yearly variables kept stable over the months and *Unemployment rate* is the monthly unemployment rate of county i. *Debt-to-tax ratio* gives the indication of whether the county is highly indebted (1) or has a low debt level (5). *Local revenue ratio* provides information on how dependent a county government is on local revenue (1) or federal or state revenue (5). The *House price index* is a year-on-year growth rate of the housing index for county i in year y. *Agriculture dependence* variable is taken from the County Typology Codes of the USDA Economic Research Service and equals 1 when a county relies most on agriculture income rather than mining, manufacturing, Federal/State government, or recreational income. The *Agriculture insurance dummy* is 1 when a county relies most on producing livestock or specialty crops. The

VARIABLES	Obs.	Mean	Std. Dev.	Min.	Max.
Yield	126,741.00	2.55	1.63	0.00	96.10
Drought category	126,741.00	0.20	0.53	0.00	5.00
Share of agriculture acres	126,741.00	0.41	0.26	0.00	0.98
Water risk measure (WRM)	126,741.00	0.08	0.26	0.00	3.89
Coupon rate	126,741.00	4.18	0.95	0.00	9.50
Years to maturity	126,741.00	16.03	5.61	2.00	68.49
Trading volume	126,741.00	77,006.41	144,787.25	1,000.00	8,967,500.00
Population	126,741.00	188,996.93	468,153.99	690.00	10094865.00
Personal income	126,741.00	44,144.52	12,987.36	19,606.80	251,728.00
Unemployment rate	126,741.00	5.52	2.36	0.90	31.40
Debt-to-tax ratio (quintiles)	126,741.00	3.20	1.34	1.00	5.00
Local revenue ratio (quintiles)	126,741.00	2.75	1.36	1.00	5.00
House price index (YoY)	126,741.00	0.04	0.04	-0.15	0.35
Agriculture dependence (dummy)	126,741.00	0.05	0.22	0.00	1.00
Agriculture insurance (dummy)	126,741.00	0.54	0.50	0.00	1.00

Table 2 Correlation matrix

This table shows the correlations between the independent variables in our study. We refer to Table 1 for a description of these variables. P-values are reported in parentheses below the correlations.

	WRM	Coupon	Years to maturity	Trading volume	Population	Personal income	Unemployment rate	Debt to tax	Local revenue ratio	Housing index (YoY)	Agriculture insurance dummy	Agriculture dependence dummy
Water risk measure	1.0000											
Coupon rate	0.0249	1.0000										
	(0.000)											
Years to maturity	0.0139	0.4251	1.0000									
	(0.000)	(0.000)										
Trading volume	0.0002	0.0004	0.0035	1.0000								
	(0.953)	(0.874)	(0.217)									
Population	-0.0066	0.0817	0.0456	0.0465	1.0000							
	(0.0196)	(0.000)	(0.000)	(0.000)								
Personal income	-0.0298	-0.0042	-0.0556	0.0229	0.2806	1.0000						
	(0.000)	(0.136)	(0.000)	(0.000)	(0.000)							
Unemployment rate	0.0574	0.1151	0.1184	-0.0131	-0.0307	-0.3138	1.0000					
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)						
Debt-to-tax ratio	0.0090	0.0567	-0.0049	0.0211	0.2852	0.4762	-0.2057	1.0000				
	(0.001)	(0.000)	(0.079)	(0.000)	(0.000)	(0.000)	(0.000)					
Local revenue ratio	-0.0495	-0.0335	0.0482	-0.0200	-0.1392	-0.2835	0.3088	-0.2262	1.0000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
House price index	0.0033	0.0093	-0.0022	0.0261	0.0981	0.0319	-0.1403	-0.0231	-0.0677	1.0000		
	(0.233)	(0.001)	(0.438)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
Agriculture insurance	-0.0328	0.0518	0.0500	0.0235	0.0892	-0.0074	0.1169	-0.0676	0.0563	0.1297	1.0000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)		
Agriculture dependence	0.0305	-0.0368	0.0133	0.0058	-0.0877	-0.0461	-0.0566	-0.1942	0.0600	0.0493	-0.0378	1.0000
	(0.000)	(0.000)	(0.000)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 3 Relation between municipal bond yields and the water risk measure

This table shows the results of regressions to examine the relation between the municipal bond yield and the Water risk measure. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed Water risk measure and the municipal bond control variables. We refer to Table 1 for a description of these variables. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. In all specifications, we include month fixed effects to control for seasonality in our data. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	0.02			0.05		
	(0.264)			(0.126)		
Water Risk Measure (Lag 3 months)		0.06***			0.09***	
		(0.006)			(0.007)	
Water Risk Measure (Lag 6 months)			0.07***			0.11***
			(0.000)			(0.000)
Coupon rate	0.12***	0.10***	0.11***	0.25***	0.24***	0.24***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years to maturity	0.06***	0.06***	0.06***	0.07***	0.07***	0.07***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.24***	-0.23***	-0.22***	-0.49***	-0.47***	-0.48***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.29	-0.17	-0.19	-0.07***	-0.06***	-0.06***
	(0.618)	(0.759)	(0.741)	(0.002)	(0.003)	(0.003)
Personal income	-3.54	-3.67	-3.35	-3.45***	-3.36***	-3.31***
	(0.304)	(0.291)	(0.344)	(0.001)	(0.000)	(0.001)
County unemployment rate	0.06***	0.06***	0.06***	0.03**	0.04***	0.04***
	(0.000)	(0.000)	(0.000)	(0.011)	(0.009)	(0.009)
Debt-to-tax ratio	-0.01	-0.00	-0.01	-0.02	-0.02	-0.02
	(0.780)	(0.897)	(0.837)	(0.182)	(0.155)	(0.112)
Local revenue ratio	-0.01	-0.01	-0.00	0.03**	0.03**	0.03**
	(0.704)	(0.711)	(0.818)	(0.016)	(0.027)	(0.018)
House Index Return (YoY)	-0.95***	-0.94***	-0.96***	-0.54	-0.63*	-0.64*
	(0.000)	(0.000)	(0.000)	(0.106)	(0.058)	(0.053)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.39	0.40	0.39	0.16	0.16	0.16
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes

Table 4 Relation between municipal bond yields and the WRM conditional on local debt

This table shows the results of regressions to examine the relation between the municipal bond yield and the WRM conditional on a county's indebtedness measured by the Debt-to-tax ratio. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed WRM, the Debt-to-tax dummy that equals 1 if the county is highly indebted, the interaction term between the WRM and the dummy, and the municipal bond control variables. We refer to Table 1 for a description of these variables. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In all specifications, we include month fixed effects to control for seasonality in our data. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. To maintain consistency and clarity in our analysis, the Debt-to-tax dummy and the interaction term are lagged corresponding to the respective lags of the WRM variable. This approach ensures that the interaction term is accurately aligned with the WRM values, providing a coherent basis for comparison. Additionally, applying the same lag to the dummy variable facilitates a clearer interpretation of the interaction term's coefficient. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4 - continued

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	-0.00974			-0.00868		
	(0.574)			(0.699)		
WRM x Debt-to-tax dummy (Lag 1 month)	0.125*			0.222*		
	(0.060)			(0.073)		
Debt to Tax Dummy (1=indebted)(Lag 1 month)	-0.0153			0.0325		
	(0.757)			(0.395)		
Water Risk Measure (Lag 3 months)		0.0374*			0.0447*	
		(0.051)			(0.056)	
WRM x Debt-to-tax dummy (Lag 3 months)		0.0995			0.170	
		(0.162)			(0.158)	
Debt to Tax Dummy (1=indebted) (Lag 3 months)		-0.0142			0.0381	
		(0.771)			(0.320)	
Water Risk Measure (Lag 6 months)			0.0629***			0.0733***
			(0.000)			(0.001)
WRM x Debt-to-tax dummy (Lag 6 months)			0.0423			0.133
			(0.303)			(0.132)
Debt to Tax Dummy (1=indebted) (Lag 6 months)			0.00452			0.0477
			(0.923)			(0.215)
Coupon rate	0.120***	0.101***	0.111***	0.246***	0.237***	0.238***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years to maturity	0.0624***	0.0621***	0.0608***	0.0663***	0.0656***	0.0651***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.241***	-0.226***	-0.217***	-0.487***	-0.466***	-0.485***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.291	-0.178	-0.188	-0.0767***	-0.0705***	-0.0698***
	(0.614)	(0.753)	(0.742)	(0.001)	(0.001)	(0.001)
Personal income	-3.603	-3.705	-3.362	-3.801***	-3.719***	-3.680***
	(0.298)	(0.287)	(0.343)	(0.000)	(0.000)	(0.000)
County unemployment rate	0.0552***	0.0594***	0.0601***	0.0341**	0.0360***	0.0358***
	(0.000)	(0.000)	(0.000)	(0.010)	(0.009)	(0.009)
Local revenue ratio	-0.0109	-0.00961	-0.00648	0.0311**	0.0288**	0.0307**
	(0.615)	(0.654)	(0.768)	(0.014)	(0.026)	(0.017)
House Index Return (YoY)	-0.957***	-0.945***	-0.961***	-0.543	-0.631*	-0.637*
	(0.000)	(0.000)	(0.000)	(0.104)	(0.056)	(0.051)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.387	0.396	0.386	0.160	0.159	0.158
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes

Table 5 Relation between municipal bond yields and the WRM conditional on local revenue streams

This table shows the results of regressions to examine the relation between the municipal bond yield and the WRM conditional on how local the revenue streams are of the counties. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed WRM, the Local revenue dummy that equals 1 if the county depends more on local revenue rather than federal or state revenue, the interaction term between the WRM and the dummy, and the municipal bond control variables. We refer to Table 1 for a description of these variables. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In all specifications, we include month fixed effects to control for seasonality in our data. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. To maintain consistency and clarity in our analysis, the Local revenue dummy and the interaction term are lagged corresponding to the respective lags of the WRM variable. This approach ensures that the interaction term is accurately aligned with the WRM values, providing a coherent basis for comparison. Additionally, applying the same lag to the dummy variable facilitates a clearer interpretation of the interaction term's coefficient. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5 - continued

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	0.0201			0.0544		
	(0.427)			(0.295)		
WRM x Local revenue dummy (Lag 1 month)	0.00732			-0.00590		
	(0.860)			(0.938)		
Local revenue dummy (Lag 1 month)	0.000224			-0.0810***		
	(0.996)			(0.005)		
Water Risk Measure (Lag 3 months)		0.0558**			0.0769	
		(0.026)			(0.127)	
WRM x Local revenue dummy (Lag 3 months)		0.0135			0.0194	
		(0.754)			(0.787)	
Local revenue dummy (Lag 3 months)		-0.00798			-0.0790***	
		(0.842)			(0.007)	
Water Risk Measure (Lag 6 months)			0.0529**			0.0927**
			(0.028)			(0.037)
WRM x Local revenue dummy (Lag 6 months)			0.0355			0.0237
			(0.267)			(0.687)
Local revenue dummy (Lag 6 months)			0.00369			-0.0808***
			(0.938)			(0.006)
Coupon	0.120***	0.101***	0.111***	0.247***	0.238***	0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years to maturity	0.0624***	0.0621***	0.0608***	0.0662***	0.0656***	0.0651***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.242***	-0.227***	-0.216***	-0.485***	-0.464***	-0.482***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.299	-0.188	-0.191	-0.0720***	-0.0655***	-0.0649***
	(0.603)	(0.738)	(0.737)	(0.002)	(0.003)	(0.003)
Personal income	-3.565	-3.709	-3.347	-3.489***	-3.384***	-3.370***
	(0.301)	(0.286)	(0.345)	(0.001)	(0.000)	(0.001)
County unemployment rate	0.0552***	0.0594***	0.0601***	0.0349***	0.0365***	0.0366***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)	(0.006)
Debt-to-tax ratio	-0.0139	-0.00984	-0.00927	-0.0208	-0.0213	-0.0231
	(0.675)	(0.764)	(0.781)	(0.169)	(0.146)	(0.105)
House Index Return (YoY)	-0.956***	-0.944***	-0.960***	-0.540	-0.626*	-0.627*
	(0.000)	(0.000)	(0.000)	(0.108)	(0.059)	(0.057)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.387	0.396	0.386	0.159	0.159	0.158
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes

Table 6 Relation between municipal bond yields and the WRM conditional on maturity

This table shows the results of regressions to examine the relation between the municipal bond yield and the WRM conditional on the average maturity of the bonds traded in county i. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed WRM, the Maturity dummy that equals 1 if the average maturity of bonds traded in the county is smaller than 5 years, the interaction term between the WRM and the dummy, and the municipal bond control variables. We refer to Table 1 for a description of these variables. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In all specifications, we include month fixed effects to control for seasonality in our data. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. To maintain consistency and clarity in our analysis, the Maturity dummy and the interaction term are lagged corresponding to the respective lags of the WRM variable. This approach ensures that the interaction term is accurately aligned with the WRM values, providing a coherent basis for comparison. Additionally, applying the same lag to the dummy variable facilitates a clearer interpretation of the interaction term's coefficient. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6 - continued

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	0.0242			0.0532		
	(0.283)			(0.128)		
WRM x Maturity dummy (Lag 1 month)	-0.414			-0.470		
	(0.206)			(0.216)		
Maturity dummy (Lag 1 month)	0.143			-0.0297		
	(0.610)			(0.923)		
Water Risk Measure (Lag 3 months)		0.0581**			0.0849**	
		(0.013)			(0.012)	
WRM x Maturity dummy (Lag 3 months)		-0.141			-0.233	
		(0.332)			(0.190)	
Maturity dummy (Lag 3 months)		0.0494			-0.117	
		(0.643)			(0.449)	
Water Risk Measure (Lag 6 months)			0.0667***			0.100***
			(0.000)			(0.000)
WRM x Maturity dummy (Lag 6 months)			-0.0997			-0.0385
			(0.523)			(0.777)
Maturity dummy (Lag 6 months)			-0.0431			-0.205***
			(0.385)			(0.000)
Coupon	0.274***	0.250***	0.256***	0.395***	0.381***	0.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.248***	-0.241***	-0.234***	-0.479***	-0.465***	-0.482***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.842	-0.724	-0.739	-0.0639**	-0.0579**	-0.0569**
	(0.164)	(0.222)	(0.219)	(0.019)	(0.032)	(0.036)
County income	-6.803*	-6.905*	-6.546*	-4.897***	-4.828***	-4.798***
	(0.052)	(0.052)	(0.069)	(0.000)	(0.000)	(0.000)
County unemployment rate	0.0668***	0.0715***	0.0717***	0.0461***	0.0481***	0.0477***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt-to-tax ratio	-0.0110	-0.00618	-0.00888	-0.0204	-0.0210	-0.0231
	(0.754)	(0.860)	(0.806)	(0.200)	(0.175)	(0.128)
Local revenue ratio	-0.0149	-0.0133	-0.00914	0.0374***	0.0352**	0.0374***
	(0.489)	(0.544)	(0.675)	(0.008)	(0.014)	(0.009)
House Index Return (YoY)	-0.997***	-0.986***	-0.999***	-0.619*	-0.696**	-0.705**
	(0.000)	(0.000)	(0.000)	(0.073)	(0.042)	(0.038)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.366	0.374	0.365	0.111	0.111	0.111
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes

Table 7 Relation between municipal bond yields and the WRM conditional on crop insurance

This table shows the results of regressions to examine the relation between the municipal bond yield and the WRM conditional on the type (low or high insured) of crops counties primarily produce. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed WRM, the Agriculture insurance dummy that equals 1 if the county produces mostly low-insured crops (specialty crops and rangeland), the interaction term between the WRM and the dummy, and the municipal bond control variables. We refer to Table 1 for a description of these variables. In the Table, the Agriculture insurance dummy is referred to as the Insurance dummy to conserve space. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In all specifications, we include month fixed effects to control for seasonality in our data. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. To maintain consistency and clarity in our analysis, the Agriculture insurance dummy and the interaction term are lagged corresponding to the respective lags of the WRM variable. This approach ensures that the interaction term is accurately aligned with the WRM values, providing a coherent basis for comparison. Additionally, applying the same lag to the dummy variable facilitates a clearer interpretation of the interaction term's coefficient. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7 - continued

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	0.0204			0.0563*		
	(0.418)			(0.066)		
WRM x Insurance dummy (Lag 1 month)	0.00796			-0.00799		
	(0.855)			(0.914)		
Insurance dummy (Lag 1 month)	0.0458			-0.00347		
	(0.232)			(0.927)		
Water Risk Measure (Lag 3 months)		0.0618**			0.0949***	
		(0.016)			(0.001)	
WRM x Insurance dummy (Lag 3 months)		0.00358			-0.0105	
		(0.938)			(0.882)	
Insurance Dummy (Lag 3 months)		0.0265			0.000687	
		(0.511)			(0.986)	
Water Risk Measure (Lag 6 months)			0.0779***			0.121***
			(0.000)			(0.000)
WRM x Insurance dummy (Lag 6 months)			-0.00819			-0.0268
			(0.801)			(0.625)
Insurance Dummy (Lag 6 months)			0.0148			-0.00404
			(0.720)			(0.915)
Coupon	0.120***	0.101***	0.111***	0.247***	0.238***	0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years to maturity	0.0624***	0.0621***	0.0607***	0.0663***	0.0656***	0.0651***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.242***	-0.227***	-0.216***	-0.486***	-0.465***	-0.483***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.306	-0.185	-0.198	-0.0712***	-0.0650***	-0.0638***
	(0.596)	(0.744)	(0.730)	(0.002)	(0.003)	(0.004)
County income	-3.376	-3.558	-3.283	-3.437***	-3.366***	-3.298***
	(0.330)	(0.309)	(0.359)	(0.001)	(0.001)	(0.001)
County unemployment rate	0.0546***	0.0590***	0.0599***	0.0340**	0.0358**	0.0357**
	(0.000)	(0.000)	(0.000)	(0.013)	(0.011)	(0.011)
Debt-to-tax ratio	-0.00998	-0.00462	-0.00757	-0.0201	-0.0208	-0.0227
	(0.779)	(0.895)	(0.835)	(0.183)	(0.156)	(0.113)
Local revenue ratio	-0.00760	-0.00773	-0.00480	0.0308**	0.0286**	0.0307**
	(0.715)	(0.719)	(0.824)	(0.015)	(0.026)	(0.017)
House Index Return (YoY)	-0.956***	-0.944***	-0.959***	-0.543	-0.631*	-0.634*
	(0.000)	(0.000)	(0.000)	(0.108)	(0.059)	(0.056)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.387	0.396	0.386	0.159	0.159	0.158
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes

Table 8 Relation between municipal bond yields and the WRM conditional on economic dependence on agriculture

This table shows the results of regressions to examine the relation between the municipal bond yield and the WRM conditional on the economic dependence of a county on farming. The dependent variable is the volume-weighted average yield for county i in month m in year y. As independent variables, we include our own computed WRM, the Agriculture dependence dummy that equals 1 if the county economically depends on agriculture income, the interaction term between the WRM and the dummy, and the municipal bond control variables. We refer to Table 1 for a description of these variables. In the table, the Agriculture dependence dummy is referred to as the Dependence dummy to conserve space. Columns (1)-(3) show the results of Eq. 1 using county fixed effects. Columns (4)-(6) show the relation using state fixed effects. In all specifications, we include month fixed effects to control for seasonality in our data. In Columns (1) and (4), we apply a one-month lag to the WRM, while in columns (2) and (5), and columns (3) and (6), we use three-month and six-month lags, respectively. To maintain consistency and clarity in our analysis, the Agriculture dependence dummy and the interaction term are lagged corresponding to the respective lags of the WRM variable. This approach ensures that the interaction term is accurately aligned with the WRM values, providing a coherent basis for comparison. Additionally, applying the same lag to the dummy variable facilitates a clearer interpretation of the interaction term's coefficient. The dummy variable indicates whether a county is economically dependent on agriculture, and this status does not change over the time period; therefore, in the county fixed effects specifications, the dummy gets omitted by construction. In the table, the values for the population, trading volume, and personal income variables have been scaled down by a factor of one million for readability. The final row shows the total observations included in the models. Intercepts are suppressed to conserve space. The standard errors are clustered by county. The p-values are provided in the parentheses. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8 - continued

VARIABLES	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield	(6) Yield
Water Risk Measure (Lag 1 month)	0.0213			0.0549		
	(0.351)			(0.138)		
WRM x Dependence dummy (Lag 1 month)	0.0488			-0.0399		
	(0.347)			(0.597)		
Dependence dummy (Lag 1 month)				0.0153		
				(0.853)		
Water Risk Measure (Lag 3 months)		0.0633***			0.0931***	
		(0.009)			(0.009)	
WRM x Dependence dummy (Lag 3 months)		0.00458			-0.0600	
		(0.943)			(0.493)	
Dependence dummy (Lag 3 months)					-0.00880	
					(0.917)	
Water Risk Measure (Lag 6 months)			0.0755***			0.112***
			(0.000)			(0.000)
WRM x Dependence dummy (Lag 6 months)			-0.0290			-0.0619
			(0.570)			(0.391)
Dependence dummy (Lag 6 months)						-0.0170
						(0.840)
Coupon rate	0.120***	0.101***	0.111***	0.247***	0.238***	0.239***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years to maturity	0.0624***	0.0621***	0.0608***	0.0662***	0.0656***	0.0652***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trading volume	-0.242***	-0.227***	-0.216***	-0.486***	-0.465***	-0.483***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.287	-0.173	-0.188	-0.0713***	-0.0650***	-0.0641***
	(0.618)	(0.759)	(0.742)	(0.002)	(0.003)	(0.003)
County income	-3.563	-3.668	-3.329	-3.457***	-3.348***	-3.291***
	(0.301)	(0.291)	(0.347)	(0.001)	(0.000)	(0.001)
County unemployment rate	0.0553***	0.0594***	0.0601***	0.0340**	0.0356***	0.0354***
	(0.000)	(0.000)	(0.000)	(0.011)	(0.010)	(0.010)
Debt-to-tax ratio	-0.00987	-0.00455	-0.00751	-0.0198	-0.0212	-0.0234
	(0.782)	(0.897)	(0.836)	(0.211)	(0.168)	(0.120)
Local revenue ratio	-0.00796	-0.00795	-0.00492	0.0307**	0.0288**	0.0309**
	(0.703)	(0.711)	(0.819)	(0.017)	(0.028)	(0.019)
House Index Return (YoY)	-0.955***	-0.943***	-0.960***	-0.545	-0.632*	-0.637*
	(0.000)	(0.000)	(0.000)	(0.106)	(0.058)	(0.053)
Observations	89,554	85,444	85,154	89,626	85,513	85,227
R-squared	0.387	0.396	0.386	0.159	0.159	0.158
Clustered County Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes			
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE				Yes	Yes	Yes