Natural Disasters and Municipal Bonds*

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ABSTRACT

Climate change is increasing the frequency of natural disasters, and the municipal bond market could be particularly vulnerable to this trend. We undertake a comprehensive analysis of how and when natural disasters affect municipal bond returns. We find substantial price effects that materialize gradually in the weeks following a disaster, translating into in-sample investor losses of almost $10 billion. These effects are influenced by a range of factors that point to the mechanisms behind the observed response, including the source of bond revenue, bond insurance, disaster severity, federal disaster aid, and local financial conditions. Our findings have significant implications for investors, policymakers, and anyone concerned with the long-term stability of financial markets.

Keywords: Natural Disasters, Climate Change, Municipal Bonds, Municipal Financing, Repeat Sales

JEL classification: G10, G14, Q54

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Climate change is causing extreme weather events to become more frequent and more severe (IPCC, 2021). In 1990–2020, the number of disaster and emergency declarations in the United States grew by almost 7% per year on average, and estimated physical damage from natural disasters caused by extreme weather events averaged over $11 million per affected county.[1] This trend is expected to intensify. A recent survey of academics, finance professionals, and regulators revealed that, over the next 30 years, physical risk ranks as the top climate-related risk for firms and investors (Stroebel and Wurgler, 2021). There is also a widespread belief that asset prices underestimate climate risks. Yet our understanding of how asset markets price physical risk remains incomplete. Studies of the economic impacts of natural disasters have demonstrated, for example, that it is not just the strength of the event that matters, but the socioeconomic characteristics of affected areas (e.g., Deryugina, Kawano, and Levitt, 2018; Jerch, Kahn, and Lin, 2023). Studying how asset markets are affected by extreme events yields insights into investor beliefs and behavior and provides valuable information to policymakers and market participants about how asset markets can be made more resilient to climate change.

We undertake a comprehensive study of the effects of natural disasters on the US municipal bond market, which was valued at $4 trillion in 2022. Given the crucial role that municipal bonds play in public financing and investment, understanding when, how, and why natural disasters affect municipal bond returns is of paramount importance for investors, municipal bond issuers, and fiscal policymakers. Yet the answers are ex-ante unclear, for four key reasons. First, despite inflicting an evident negative economic shock in the short run, the longer-run economic impacts of a natural disaster may be negligible or even positive (e.g., Strobl, 2011; Deryugina et al., 2018). Second, economic impacts may not correspond to changes in outcomes that are relevant to municipal bonds (e.g., tax or project revenue). Third, post-disaster aid may counteract the economic shock of the disaster, while municipal bond insurance may make the economic consequences of the disaster irrelevant to outstanding bonds. Finally, the unique nature of the municipal bond market—extreme illiquidity and a retail-heavy investor base—makes the speed and extent of bond price reactions following disasters an interesting open empirical question.

Combining county-level weekly bond returns with data on over 2,000 extreme weather events that

[1] Sources: The Federal Emergency Management Agency and the Spatial Hazards Events and Losses Database for the US. Damage includes both crop and property damage and is reported in 2018 dollars.

occurred in 2005–2018, we use event-study and difference-in-differences methodologies to study how natural disasters affect bond prices. We implement the repeat sales approach, originally designed to circumvent the sparse-trading problem in real-estate markets, to overcome the challenge that the typical municipal bond trades fewer than three times per year. Applying this method yields more than a ten-fold increase in the number of counties for which we observe weekly bond prices. It also enables us to examine *ex-post* returns immediately following disasters, which are essential for understanding how physical climate risk—as opposed to regulatory and transitional climate risks—is priced *ex-ante* in financial markets and how that response is moderated or exacerbated by existing policies and by bond, disaster, and location characteristics.

We find that natural disasters reduce the returns of uninsured municipal bonds for at least 20 weeks following the average event in our sample. The average decline in returns is 31 basis points over the post-event period. Consistent with the illiquid nature of the municipal bond market, we find that bond returns fall gradually rather than immediately in the post-disaster period, and the return response peaks after around ten weeks. The overall price decline is driven almost solely by uninsured revenue (REV) bonds, which are backed by revenue from specific public projects: on average, 20-week cumulative returns of such bonds are 51 basis points lower following a natural disaster. In contrast, price impacts are economically negligible and statistically insignificant for uninsured general-obligation (GO) bonds, which are backed by overall municipal tax revenue, suggesting that the stability of bond returns depends heavily on revenue diversification.[2]

The magnitude of the average effect implies investor losses of $9.25 million per disaster-affected county or $9.6 billion across all disaster-affected counties in our bond sample.[3] The per-county investor loss is almost half of the estimated physical damage, which averages $18.8 million per county in our sample. Although the latter figure does not include indirect damage to the economy (e.g., through reduced economic activity) or account for post-disaster aid, the comparison underscores the fact that estimated investor losses are not small.

To understand the mechanisms behind the overall response, we then investigate how bond insurance, disaster severity, and the federal government's aid response affect the post-disaster trajectory

[2] Monthly-level estimates yield very similar insights.

[3] The dollar value estimation is based on the par value of uninsured revenue bonds.

of municipal bond returns. Insured bonds exhibit no significant negative post-disaster returns, implying that market participants believe that insurance largely immunizes bond cash flows against natural disasters. The non-response of uninsured GO bonds and insured bonds also allows us to rule out the possibility that natural disasters increase investors' demand for liquidity because municipal bond investors—who tend to live in the general geographic proximity—are themselves affected by the event. Disaster severity—measured by real physical damage per capita—also plays an important role in determining the price impact: monthly returns of uninsured REV bonds issued by counties that experience above-median disaster severity fall by 61 basis points, while those issued by counties that experience below-median severity have an insignificant post-disaster decline of 35 basis points. The price impact depends most heavily on federal disaster aid receipt: despite suffering substantially less damage on average, uninsured REV bonds in counties that receive no disaster aid experience a 1.2 percentage point post-disaster drop in returns. By contrast, uninsured REV bonds in counties with above-median disaster aid per dollar of damage experience an insignificant post-disaster drop of 30 basis points. We also find that lower ex-ante mitigation efforts are predictive of larger post-disaster price declines. Overall, the pattern of price responses is consistent with the combined effects of investor reactions to higher municipal bond risk and higher risk aversion among disaster-affected investors (Bharath and Cho, 2021).

Finally, we show that not all GO bonds are immune to disaster shocks. When the most severe natural disasters hit counties with high financial burdens, substantial negative price effects materialize. Specifically, counties that rank in the top tercile of debt-to-tax-revenue ratios experience a 55 basis point post-disaster decline in uninsured GO bond returns following a disaster that ranks in the top tercile of per-capita damage. Geographic diversification in revenue sources also plays an important role in GO bond price stability. Uninsured GO bonds issued by municipalities whose revenues depend to a greater extent on local sources (versus relying on transfers from state or federal governments) exhibit substantial post-disaster price declines of approximately 0.55 percentage points. In contrast, we do not find such heterogeneity among uninsured REV bonds. We thus conclude that municipal bonds backed by sufficiently diversified revenue sources are not sensitive to natural disasters—with the exception of those issued by municipalities in weak financial condition. The most likely explanation for this exception is that it is harder for municipalities carrying high debt burdens to diversify away the shock created by very severe natural disasters.

Our paper contributes to the growing number of studies that strive to understand how climate change will affect financial markets.[4] Among the few papers studying the municipal bond market, ours provides the first analysis of secondary market returns. As such, our results speak directly to the portfolio performance and wealth of bond investors. Moreover, we show ex-post return variations that should be priced ex-ante in bond prices (as long as such variations are non-diversifiable), thus providing an important missing economic link indicating how climate risk is priced in ex-ante bond yields. Considering ex-post returns also makes it feasible to measure the influence of rare events, as studies of rare events focused on ex-ante pricing are likely to be underpowered, lack high-quality information about risk, and lack meaningful variation in risk over time, making identification difficult.[5]

Our study complements analyses of the effects of sea level rise (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021) and heat risk (Acharya, Johnson, Sundaresan, and Tomunen, 2022).[6] In each of these studies, the authors find that municipal bonds facing higher sea level rise or heat risk generate higher yields. But the variation in expected future sea level rise and heat risk is largely cross-sectional, raising concerns about omitted variable bias, even with extensive controls. To mitigate such concerns, Painter (2020) compares the capitalization of SLR risk into long-term versus short-term bonds and before versus after the release of the 2006 Stern Review highlighting the dangers of climate change, while Goldsmith-Pinkham et al. (2021) compare yields of bonds issued by school districts located in the same county but facing different SLR risk. By contrast, our approach requires much less restrictive identification assumptions. Sea level rise and heat risk are also slow-moving phenomena that may not be salient to investors,[7] potentially eliciting different responses from those that follow natural disasters, which are salient phenomena that can affect

[4]See Hong, Karolyi, and Scheinkman (2020), Furukawa, Ichiue, and Shiraki (2020), and Giglio, Kelly, and Stroebel (forthcoming) for a review.

[5]For example, an event that results in a 50 basis point ex-post decline in returns and occurs with a 10 percent probability should increase ex-ante yields by roughly 0.5 basis points, an effect that is statistically difficult to detect even in a very large sample.

[6]Several recent papers also focus on the real estate market, showing how it can be used to determine discount rates for investments in climate-change abatement (Giglio, Maggiori, Rao, Stroebel, and Weber, 2021) and estimating how projected SLR and disaster risk affect local real estate prices and lender behavior (Bernstein, Gustafson, and Lewis, 2019; Murfin and Spiegel, 2020; Nguyen, Ongena, Qi, and Sila, 2021). Our focus on the municipal bond market complements these findings.

[7]For example, DellaVigna and Pollet (2007) posit that investors under-react to slow-moving predictable demographic changes precisely because they are slow-moving and non-salient.

investor risk perception immediately (Dessaint and Matray 2017). Sea level rise risk also affects a smaller set of communities, whereas the projected increases in disaster frequency and intensity are widespread.

The study most closely related to ours is Jerch et al. (2023), who use annual data to show that US hurricane strikes worsen local economic conditions and lead to lower municipal debt ratings in the longer run. While some of our conclusions—which are based on a much larger set of natural disasters and locations—are consistent with this narrative, our detailed heterogeneity analyses allow us to speak to mechanisms underlying the overall findings in much more detail. We also identify a broad set of conditions under which municipal bonds are either partly or fully shielded from negative consequences natural disasters, yielding a richer set of policy implications. Additionally, we hold the sample of bonds fixed, whereas the conclusions of Jerch et al. (2023) could be affected by endogenous post-disaster decisions of municipalities to issue bonds. For example, if municipalities that receive less post-disaster aid (and are thus in worse financial shape) are more likely to issue bonds to make up for the lower federal funding, then the estimated rating impacts will be too large. Finally, bond ratings are generally very coarse, slow to adjust to new information, and could be affected by non-price factors.[8] In contrast, bond prices reflect timely, continuous variations in investor wealth.

We also contribute to the debate over whether asset markets are under-reacting to climate risk. Although many academics and practitioners believe this to be the case (Stroebel and Wurgler, 2021), empirical evidence is scarce. Alok, Kumar, and Wermers (2020) conclude that some fund managers over-react to the occurrence of extreme events, but Kruttli, Roth Tran, and Watugala (2021) show that investors appear to substantially *underestimate* hurricane-induced uncertainty. Our consideration of high-frequency price dynamics and impact heterogeneity allows us to indirectly test whether the price responses are likely to be under- or over-reactions. Our findings show that reactions of municipal bond investors—many of whom are households—to natural disasters are largely internally consistent, for two reasons. First, investor reactions are limited largely to cases where the municipal bonds are uninsured and backed by revenues tied to specific projects and where

[8] See, e.g., Beaver, Shakespeare, and Soliman (2006) and Bruno, Cornaggia, and Cornaggia (2016). The 2002 Rating Agencies Survey from the Association for Financial Professionals also reports that most financial professionals are concerned with the quality and timeliness of credit ratings.

a county receives less federal disaster aid than expected given a disaster's severity. Second, such a reaction is stable and does not reverse itself for at least six months following an extreme event.

The rest of the paper is organized as follows. Section I outlines the data we use. Section II describes our repeat sales approach and main empirical model. Section III presents the baseline results and tests of various mechanisms. Finally, Section IV discusses the implications and concludes.

I. Data

A. Municipal Bond Data

We use the Municipal Securities Rulemaking Board's (MSRB's) municipal bond transaction database to construct bond returns. The database provides transaction- and bond-level information such as the CUSIP identifier, the trade date and time, the dollar price of the transaction, and the par value of a trade. Because our smallest unit of time is one week, we convert transaction-level data to weekly data. To do so, we first calculate volume-weighted price averages and derive daily bond prices following Bessembinder, Kahle, Maxwell, and Xu (2009) and then use Friday prices to obtain weekly prices. If a Friday price is not available because of the lack of trades, we use the last available price of the week. We exclude bond prices within 30 days of issuance. We also assume that the price of bonds at maturity is their par value.

We obtain data on other bond characteristics and terms and conditions from the Mergent Municipal Bond Database. These characteristics include callability, coupon frequency, coupon rate, coupon type, maturity date, insurance provider, total offering amount, source of repayment, use of proceeds, and tax treatment (whether a bond is tax-exempt or not). The database covers municipal bonds issued between July 1960 and March 2016. We consider only tax-exempt bonds (*tax_code_c*="EXMP") with fixed or zero coupons (*coupon_code_c* equal to "FXD," "OID," "OIP," or "ZER").[9] We classify bonds as general obligation (GO) or revenue (REV) bonds based on the *security code* or *source of repayment* in the Mergent data. Specifically, bonds are categorized as GO bonds if *security_code_i* = "K," *security_code_i* = "D," or *source_of_repayment_i* = "K." Bonds

[9]While original-issued discount (OID) and original-issued premium (OIP) bonds do not necessarily pay fixed coupons, we include them in our sample because OID bonds are typically zero-coupon bonds and the majority of the bonds in our data (45.24%) are OIP bonds. See Landoni (2018) for additional details indicating why OIP bonds are commonly used in the municipal bond market.

are categorized as double-barreled (backed by both the revenue of a project and the taxing power of a local government) if *source_of_repayment*="A" or *security_code*="A." If a bond is classified as neither GO nor double-barrelled, we classify it as a REV bond. We further categorize bonds into insured and uninsured classes based on the *bond insurance code* in Mergent.[10] We drop bonds that do not pay semi-annual coupons with 30/360 accrual calculation, which account for approximately 0.05% of the sample.

We merge the MSRB and the Mergent databases by CUSIP. Because the coverage of our version of the Mergent data ends in March 2016, our sample includes only bonds issued before that date. However, the MSRB data allow us to track bond prices up to June 2020. Our final sample includes 709,608 bonds issued by 2,223 counties, with price data spanning January 2005 through June 2020.

B. County-level Economic and Financial Data

We obtain county-level economic and financial data from two sources. Regional Economic Information System (REIS) data from the Bureau of Economic Analysis (BEA) provide annual county-level information on personal income and populations. We obtain each county's annual unemployment rate from the Bureau of Labor Statistics. We supplement these data with annual financial information from the Census of Governments, which reports local government debt, cash and securities, and tax revenue.

C. Natural Disaster Data

To identify counties that experience natural disasters, we use the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS reports counties affected by an extreme weather event, the month and year of the event, event type (e.g., hurricane, flood, tornado), and estimates of property damage, crop damage, injuries, and fatalities. The data run from January 1960 through December 2018. Because we do not observe the exact date of a disaster, we assume that it occurred on the last day of the month. This assumption implies that our estimates of how quickly the municipal bond market reacts to the occurrence of a natural disaster serve as upper bounds.

[10]We classify a bond as insured if *bond_insurance_code* is not missing and as uninsured if *bond_insurance_code* is missing.

We focus on meteorological events and aggregate reported damage at the county-month level. To measure disaster severity, we calculate per-capita disaster damage as the sum of real crop and property damage (in 2018 dollars) divided by population. Because SHELDUS includes many events that cause only minor damage, we define "disasters" as county-month events that are associated with more than $3 per-capita in damage, which corresponds to the 75th percentile threshold across SHELDUS events. Admittedly, the threshold is somewhat arbitrary, but our findings are robust to other definitions, such as considering the top 10% or top 20% of events by per-capita damage. Based on our preferred definition, our sample includes 25,426 county-months with disasters in the 2005–2018 period.

Gallagher (2021) shows that SHELDUS under-reports extreme weather events non-randomly, but unfortunately SHELDUS remains the most comprehensive database of county-level natural disasters. The relevant concern for our study is that, if control counties also experience a given natural disaster, our estimated impacts would be biased toward zero. Fortunately, Gallagher (2021) also shows that SHELDUS is more likely to report damage for more extreme weather events, which makes control group contamination less likely. Nonetheless, this concern motivates us to restrict our sample of control counties to those that are located at least 500 miles away from a disaster-affected county: Extreme weather is spatially correlated, and a large buffer zone around disaster-affected counties therefore reduces the likelihood that we will classify a disaster-affected county as a control. Furthermore, because our preferred measure of "natural disaster" consists of a quarter of reported SHELDUS events and our results are robust to considering an even smaller subset of damaging events, it is unlikely that our findings are affected by unreported events.

We obtain data on federal disaster aid to households and local governments from the Federal Emergency Management Agency (FEMA). In the United States, governors of disaster-affected states can request federal emergency or major disaster declarations. To be eligible for federal disaster aid, a state must demonstrate that an event is so severe that state and local resources are insufficient to respond to it effectively. Although FEMA uses some objective metrics to assess eligibility—such as per-capita damage—there is no explicit formula, and the ultimate decision regarding whether to declare a federal disaster is up to the US president. That said, for many large-scale disasters a federal disaster declaration is swift and ex-ante all but certain. For example, a deadly tornado in Kentucky on the evening of December 10, 2021 received a federal disaster declaration the next day. Disasters that are more sharply localized, however, may not be eligible for federal disaster aid if the aggregate damage is relatively low.[11] Conditional on the granting of a federal disaster declaration, aid eligibility is determined on a county-by-county basis based on the severity of the impact in each affected county.

Residents and local governments of counties with major disaster declarations are eligible for grants from one or more disaster relief programs administered by FEMA. The grants can be used for the repair and restoration of damaged infrastructure and public property (Public Assistance Program), projects aimed at preventing future disasters (Hazard Mitigation Program), and financial assistance to homeowners and renters for housing and other needs (Individual Assistance Program).

FEMA data report a disaster's location, declaration date, and amount of approved disaster aid. Data on the individual assistance program are maintained at the ZIP code level, which we then convert to county-level data. If a ZIP code falls into multiple counties, we assign it to the county with the largest population. Data on the public assistance and hazard mitigation assistance programs are maintained at the project level and report the county, declaration date, total project cost, and federal contribution to a project. We combine grants from all three programs to create a county-year measure of federal disaster aid. To account for the fact that more severe disasters receive more aid on average, we normalize the aggregated transfers by total damage, obtaining federal disaster aid per dollar of damage.

Conditional on county-level damage, there are four key sources of variations in county-level federal disaster aid. First, an extreme event may not have had a sufficiently large impact on the entire state in which it occurs to make it eligible for federal aid, in which case we would observe the affected counties receiving zero federal transfers. Second, a county may not have been declared eligible for all three assistance programs (Public Assistance, Individual Assistance, and Hazard Mitigation), reducing the ex-post amount of federal transfers we observe compared to a county that is eligible for all three is granted. Third, federal disaster grants can be used to cover only uninsured damage, and some uninsured damage—such as to commercial buildings—is not eligible. There is also a limit

[11] Cases where governors petition for federal disaster declarations but are denied are rare, likely because governors can first communicate with FEMA officials to assess the likelihood that a request will be granted before applying.

on how much individual assistance each disaster-affected household can receive. Fourth, systematic and idiosyncratic variations in the application and approval process can translate into differences in funds received. For example, some areas may disseminate information about aid eligibility more effectively and help their residents apply. These sources of aid heterogeneity are not observable to us, however, and we discuss what they might mean for the interpretation of our findings when we present the results of our disaster aid analysis. We also discuss the implications of imperfect observation of damage.

II. Empirical Design

A. Estimating County-Level Bond Returns Using Repeat Sales

Unlike stocks and other exchange-traded assets, municipal bonds trade extremely infrequently and irregularly (see, e.g., Harris and Piwowar 2006 and Green, Hollifield, and Schürhoff 2007). The average municipal bond trades only 2.9 times per year. This lack of transactions makes it almost impossible to construct a large panel of regularly timed, high-frequency returns at the county level. Moreover, to understand investor performance in municipal bonds it is crucial to examine *returns* (not just yields), which requires consecutive price observations of the same bond, an even more difficult task to achieve given the limitations of municipal bond data. We address this issue with the repeat sales model developed in the real-estate literature, which was designed to address a similar sparse-trading problem and yields housing price indices for metropolitan areas (e.g., Case and Shiller 1987, Meese and Wallace 1991, Goetzmann 1992, and Geltner and Goetzmann 2000). Robertson and Spiegel (2017) and Spiegel and Starks (2016) apply the repeat sales approach to corporate bonds, and we extend this approach to municipal bonds to construct county-level weekly return series.

We first obtain daily bond prices by taking volume-weighted price averages and then use Friday prices or the latest available prices before Fridays for weekly prices, as explained in Section I.A. Our estimation of weekly return series is based on the following model:

$$p_{i,s} = p_{i,b} \prod_{t=b+1}^{s} (1 + r_t^c)\varepsilon_{i,t},$$

where $p_{i,s}$ and $p_{i,b}$ are clean prices (i.e., without accrued interest) of bond i in weeks s and b ($s > b$), respectively. The overall weekly return in county c and week t is r_t^c. The term $\varepsilon_{i,t}$ represents the bond-specific idiosyncratic return component. Using clean prices is advantageous because it enables us to construct bond returns that are free from price changes caused by periodic coupon payments and accrued interest.

The model above is equivalent to a market model expressed in log returns. By rearranging and then taking the log of the expression above, we have:

$$R_{i,b:s} = \sum_{t=b+1}^{s} R_t^c + e_{i,b:s},$$

where $R_{i,b:s} = \log(p_{i,s}/p_{i,b})$, $R_t^c = \log(1 + r_t^c)$, and $e_{i,b:s} = \sum_{t=b+1}^{s} \log(\varepsilon_{i,t})$.

Our goal is to use $R_{i,b:s}$ to estimate the weekly county-level return R_t^c for $t = \{b+1, ..., s\}$. The weekly return R_t^c is estimated in panel regressions as the coefficient on the weekly indicator variable for week t. Each of the $b - s$ weekly indicator variables is equal to one in the one week that falls between $b + 1$ and s and equal to zero in all other weeks. We use weighted least squares (WLS) regressions with the weight being the square root of bond issue amounts divided by the square root of the time interval between $b + 1$ and s. Thus, larger issues and shorter-interval trade pairs will receive higher weights, as in Robertson and Spiegel (2017). To estimate returns in year y, we use all observations from years $y-2$, $y-1$, y, $y+1$, and $y+2$ in rolling-window regressions, which enables us to implement the repeat sales estimation while keeping computational costs reasonable.[12] In addition to constructing an aggregate bond-return series for each county, we also apply the repeat sales methodology to GO and REV bonds separately and construct county-level returns for each of these bond types.

Using the repeat sales method, we obtain weekly county-level bond returns for 920 counties, yielding a major improvement over the conventional method, which requires trade data for consecutive weeks for the same bond. Panel A in Figure I shows that repeat sales estimations generate return series for more than 30% of US counties that have outstanding municipal bonds. In contrast, the

[12]Repeat sales estimates around the boundaries of an estimation window tend to be noisier because by construction there are fewer trade pairs covering the boundaries (fewer observations of $R_{i,b:s}$). We choose a relatively long estimation window of five years so that noise from the boundaries do not influence year y estimates to any great extent. In untabulated results, we employ a shorter three-year estimation window and our results remain similar.

conventional method provides county-level returns for only 52 counties (3.6% of the counties in our sample). Given that extreme weather events are, by definition, rare, this stark contrast in coverage implies that it is very difficult to study the effects of natural disasters using the conventional method of bond-return construction (an implication we later verify empirically). Panel B in Figure I shows that only 2.9% of municipal bonds are traded weekly and only 0.88% of municipal bonds are traded daily. Even at monthly frequency, only 8.1% of bonds are traded. Thus, a repeat sales approach is a major breakthrough that allows us to obtain county-level returns for a large sample of counties.

[Insert Figure I here]

B. Main Empirical Model

Our main dependent variable is the difference in cumulative bond returns between a disaster-affected county and unaffected benchmark counties. We choose benchmark counties by considering all disaster-unaffected counties that are located at least 500 miles away and identifying 20 counties that most closely match the disaster-affected county in terms of lagged average coupon, average credit rating, average maturity, population, income per capita, and the unemployment rate.[13] For each county c affected by a disaster in week-year t, we then compute weekly cumulative abnormal returns, $WCAR_{t,c,\tau}$, from 15 weeks prior to t through τ weeks after, for $\tau \in [-15, 20]$:

$$WCAR_{c,t,\tau} = \sum_{s=-15}^{\tau} (R^c_{t+s} - R^b_{t+s}).$$

The variable R^c_{t+s} is the weekly return of county c in week $t + s$ (i.e., s weeks after the disaster), estimated using the repeat sales approach. R^b_{t+s} is the weekly benchmark return, which equals the average repeat sales return of the 20 benchmark counties in week $t + s$.

We use the following specification to estimate the effects of a natural disaster that affects county c

[13] Although we construct the benchmark to match multiple bond characteristics, such as coupon rate or maturity, we explicitly test whether bond-specific callability could bias our results. After removing all bond-months whose times to first call is less than one month, we obtain results consistent with our main findings (not reported for brevity; available upon request).

in week-year t on subsequent cumulative abnormal returns:

$$WCAR_{c,t,\tau} = \sum_{t' \in [-15,20], t' \neq -2} \beta(t') W_{c,t,\tau}(t') + \sum_{p=-5}^{P} \gamma(p) D_{c,t,\tau}(p) + \sum_{q=0}^{Q} \delta(q) E_{c,t,\tau}(q) + \alpha_c + \epsilon_{c,t,\tau}, \quad (1)$$

where $W_{c,t,\tau}(t')$ is an indicator variable that equals one when $t' = \tau$ and zero otherwise. The coefficient, $\beta(t')$, thus captures the effects of the natural disaster on the cumulative returns for each period $t' \in [-15, 20]$ (equivalently, $\tau \in [-15, 20]$). We set the reference category to $t' = -2$. $D_{c,t,\tau}(p)$ is an indicator variable that equals one if county c experiences another natural disaster p weeks before $t + \tau$ and zero otherwise. Similarly, $E_{c,t,\tau}(q)$ is an indicator variable that equals one if county c is within 200 miles of one or more other counties that experience another natural disaster q weeks before $t + \tau$ (regardless of whether we have bonds from those other counties in our estimation sample). These two sets of variables help us separate the effects of natural disasters from the effects of other disasters that hit the same or nearby counties. We set $P = 50$ and $Q = 40$.[14] Values of $P \in [20, 65]$ and $Q \in [5, 65]$ yield similar results. Because returns that are common to a specific week-year are already accounted for when we subtract benchmark county returns to obtain cumulative abnormal returns, our only additional controls are county fixed effects, α_c. Only observations that fall within the time window of interest, $\tau \in [-15, 20]$, are included in the estimation. Standard errors are three-way clustered by week-year t, the number of weeks since the disaster τ, and county c.

One challenge involved in implementing the repeat sales approach at weekly frequency is that the week indicator variables are subject to multicollinearity problems if there are no bond trades in a given county for consecutive weeks. To address this challenge, we drop extreme weather events for which more than 10% of the observations are subject to multicollinearity in repeat sales estimations within the time window.[15]

To attribute the post-disaster coefficients $\beta(t')$ for $t' \geq 0$ to the causal effects of a disaster on municipal bond prices, it must be the case that, absent the disaster, municipal bond prices in disaster-affected counties would have evolved similarly to those in benchmark counties. While this

[14] This choice is based on a trade-off between bias and power. Using larger P and Q controls for more possible spillover effects but reduces degrees of freedom.

[15] Removing this filter does not change the point estimates meaningfully, but adds noise to the estimation.

identification assumption cannot be tested directly, the unpredictable nature of disasters makes it unlikely that their timing is correlated with other county-specific shocks. Estimating pre-disaster coefficients also allows us to assess whether disaster-affected counties exhibit any differential trends relative to benchmark counties prior to the disaster. Finding that $\beta(t') = 0$ for $t' \leq -2$ would provide strong evidence for the identification assumption in our context.

To increase statistical power and concisely summarize the price effects of natural disasters, we also estimate regressions using monthly cumulative abnormal returns, $MCAR_{c,t,\tau}$:

$$MCAR_{c,t,\tau} = \sum_{t' \in [-1,4]} \beta(t') M_{c,t,\tau}(t') + \sum_{p=-1}^{P} \gamma(p) D^{M}_{c,t,\tau}(p) + \sum_{q=0}^{Q} \delta(q) E^{M}_{c,t,\tau}(q) + \alpha_c + \epsilon_{c,t,\tau}, \qquad (2)$$

where t and τ now correspond to month-year and months since the disaster, respectively. The variable $M_{c,t,\tau}(t')$ equals one when $t' = \tau$ and zero otherwise. The coefficient $\beta(t')$ thus captures the effects of the disaster on cumulative returns over this time period, relative to $t' = -2$. All other variables are the same as in Equation (1) but are defined at the monthly level.[16]

Finally, to summarize total price effects during the event window, we compare $MCAR$ at $\tau = 4$ against $MCAR$ at $\tau = -2$. In particular, we define an indicator for post-disaster ($\tau = 4$), $Post_{c,t,\tau}$, while setting $\tau = -2$ as the reference category:

$$MCAR_{c,t,\tau} = \beta Post_{c,t,\tau} + \sum_{p=-1}^{P} \gamma(p) D^{M}_{c,t,\tau}(p) + \sum_{q=0}^{Q} \delta(q) E^{M}_{c,t,\tau}(q) + \alpha_c + \epsilon_{c,t,\tau}. \qquad (3)$$

This specification further reduces noise in prices and therefore achieves greater statistical power. Because clustering by the number of months from the disaster would leave us with very few clusters along this dimension, standard errors in Equations (2) and (3) are clustered by county and year-month.[17]

C. Summary Statistics

Table I summarizes statistics of the key variables. The results reported in Panel A indicate that the average county-level weekly return is -0.001% with a standard deviation of 1.54%. REV bonds

[16] P equals 12 and Q equals 10 in this monthly-level regression.

[17] Additionally clustering by the number of months from the disaster does not, however, meaningfully alter our results.

earn higher returns on average but are also riskier than GO bonds: the average and standard deviation of REV bond returns are 0.002% and 1.89% per week, respectively, while those of GO bonds are -0.002% and 1.39% per week. Note that these return estimates do not include coupons as we employ clean prices. After including coupons, the average weekly returns are 0.079% and 0.064% for GO and REV bonds, respectively.

[Insert Table I here]

In Panel B of Table I we report summary statistics for county-months with natural disasters, using our preferred damage per capita cutoff of the 75th percentile. While most of the disaster-months in our sample are not associated with injuries, the most severe disaster injured 720 people. Fatalities are not as frequent as injuries, but the maximum number of fatalities, 86, is large. The average disaster-month inflicted $137.1 million in property damage with a standard deviation of $1.2 billion. Both aggregate and per-capita damage have long right tails: the median per-capita damage of $11 is substantially smaller than the average of $269, for example.

Panel C summarizes bond and economic characteristics for the sample of county-months with natural disasters. On average, 50% and 57% of GO and REV bonds, respectively, are insured. The average maturity of GO bonds is 6.85 years while that of REV bonds is 0.98 years longer. REV bonds tend to be subject to higher credit risk, with average ratings lower than GO bond ratings (credit ratings are converted to numerical values by assigning 1 to AAA, 2 to AA+, and so on). Municipalities have relatively high numbers of bonds outstanding; the median and average numbers of municipal bonds outstanding for each county are 750 and 1182. Federal disaster aid to disaster-affected counties averages $9.5 million per year. Local governments in our sample have an average debt-to-cash-and-security ratio of 1.61 (*Debt/Cash and Security*) and an average debt-to-tax revenue of 3.47 (*Debt/Tax Revenue*).

III. Results

A. Baseline Analysis Using the Conventional Approach

Our repeat sales approach represents a major breakthrough, allowing us to measure post-disaster price impacts at weekly and monthly frequencies across a large panel of US counties. The critical challenge with the conventional approach to measuring bond returns is the lack of regularly and frequently measured bond transactions, which makes event-study-like analyses that we conduct in the previous section almost impossible.[18] Table II demonstrates this problem empirically. Specifically, we re-estimate Equation (3) using the conventional approach, which requires consecutive bond-level monthly observations to construct county-level returns for both disaster-affected counties and their benchmark counties. Using this approach yields at most 38 observations (fewer than 10 disaster-counties), which is insufficient for formal analysis. In contrast to the number of observations generated by the repeat sales method, the number of raw observations here is about 3% for REV bonds and 1% for GO bonds. Unsurprisingly, the standard errors of the estimates are large, and we can neither detect a significant price effect nor rule out a large one. The conventional approach based on bond-by-bond return calculations is thus not viable in the context of natural disasters.

We now further explain why the conventional approach is not suitable to our setting vis-à-vis the settings of previous studies. Cornaggia, Cornaggia, and Israelsen (2018), for example, successfully construct cumulative abnormal daily returns of a municipal bond portfolio (by including any bonds with at least six days of available transactions) over a 120-day event window around the March 2010 Moody's rating recalibration. Unlike their empirical setting, which requires only one aggregate bond portfolio using all treated bonds, ours requires bond portfolios for a sufficiently large number of US counties, which cannot be constructed using the conventional approach even at the monthly level, as shown in Table II. Several other studies (e.g., Goldsmith-Pinkham et al., 2021) employ monthly averages of municipal bond yields for a given county. Unlike these studies, ours focuses on the performance of municipal bonds, which requires price changes (i.e., returns) of the same bonds in consecutive weeks and months. Average yields constructed from municipal bond data do not necessarily reflect bond performance: because the composition of bonds in each month changes given the sparseness and unevenness of the transactions, monthly yields of a county are not necessarily constructed from the same set of bonds at each point in time. The repeat sales

[18] There are alternative sources (usually data vendors) that provide daily bond prices based on proprietary models (i.e., matrix bond prices), but these prices are prone to model misspecification. Thus, any statistical inference based on such matrix prices will be subject to the joint hypothesis problem: one cannot be sure whether observed price impacts (or the lack thereof) are real or reflect errors in a data provider's matrix pricing models. Moreover, matrix prices are also subject to stale pricing and do not reflect market information in a timely way.

method overcomes this issue by extracting the return component that is common to all bonds issued by the same county.

[Insert Table II here]

B. Baseline Repeat Sales Results

Although natural disasters create short-term negative shocks to local economies by destroying physical capital and damaging infrastructure, it is ex-ante unclear how strongly municipal bond prices will respond to disasters, for four reasons. First, it is ultimately local government revenue for GO bonds and project revenue for REV bonds that matter for municipal bond cash flows. The extent to which natural disasters negatively affect sub-national government revenue is not a settled empirical question: while Jerch et al. (2023) find that local government revenue declines, others finding no statistically significant changes in revenue (Miao, Hou, and Abrigo, 2018; Masiero and Santarossa, 2020; Miao, Chen, Lu, and Abrigo, 2020). Second, the pricing of municipal bonds is forward-looking, and thus price responses should reflect both the short- and long-run effects of natural disasters. Yet the empirical literature that studies how natural disasters affect local economies in the long run has also yielded mixed findings.[19] Third, severe disasters are typically followed by federal aid from FEMA and by other government transfers (Deryugina 2017), which can offset or even eliminate long-run negative economic effects. Likewise, bond insurance can play an important role, potentially rendering a local government's financial condition irrelevant to bond returns. Fourth, trading in municipal bonds is extremely sparse; thus, it remains an open empirical question how quickly bond prices respond to natural disasters. These considerations also point to potential mechanisms behind any aggregate impacts and motivate us to study heterogeneity in post-disaster bond returns along the dimensions of cash flow sources, insurance, disaster severity, external disaster aid, and local financial conditions.

Figure II plots the cumulative abnormal returns of uninsured municipal bonds around the event window (15 weeks before to 20 weeks after natural disasters) using estimated coefficients $\beta(t')$ from

[19]For example, Boustan, Kahn, Rhode, and Yanguas (2020) find that natural disasters reduce per-capita county-level income in the United States, Strobl (2011) finds that US hurricanes have only a short-run (one-year) effect on local growth rates, and Deryugina (2017) finds no significant change in county-level per-capita income ten years after a hurricane strike. On the other hand, Roth Tran and Wilson (2022) estimate that disaster-affected counties experience long-term growth in per-capita income. See Cuaresma (forthcoming) for a comprehensive review.

Equation (1). Compared with uninsured bonds in benchmark counties, county-level bonds prices decline after disasters, with the magnitude growing to approximately 0.25% over fifteen weeks (Panel A). The price declines are persistent, lasting over twenty weeks, which indicates elevated risk for municipal bonds in disaster-affected areas. The declines are also gradual, consistent with low market liquidity or an initial underreaction by bond investors.[20] Reassuringly, we do not find pre-disaster differences in bond prices, supporting the plausibility of the parallel trends assumption that is necessary to attribute the post-disaster coefficients to the effects of the disaster itself.

[Insert Figure II here]

We next consider the returns of REV and GO bonds separately (Panels B and C of Figure II), respectively. Price declines are substantially larger for REV bonds (–0.42% fifteen weeks after a disaster) and, the price impact does not revert for at least twenty weeks following the disaster. In contrast, natural disasters barely affect GO bond prices. Because GO bonds are backed by general tax revenue, whereas REV bonds are typically backed by cash flows of specific projects, these results suggest that the typical natural disaster in our sample is not expected to worsen broader economic conditions in municipalities and point to cash flow source diversification as an important determinant of municipal bond returns in the aftermath of natural disasters. A key implication is that municipal debt backed by diversified cash flow sources—general tax revenues—will exhibit greater resilience to natural disasters than municipal debt backed by single projects or assets.

To address the potential for high-frequency noise in weekly returns, we repeat our analysis using monthly returns (Table III). In Panel A, we use one post-disaster indicator to estimate the average price impact in the post-disaster period, as in Equation (3). The results echo those shown in Figure II, indicating a price drop of approximately 0.31% after a disaster. As before, the price effect is concentrated in REV bonds (estimated price decline of 0.51% with a *t*-statistic of –2.56). As before, we find economically smaller (–0.13%) and statistically insignificant price effects for GO bonds.[21]

[20] It is unlikely that our construction of the price series makes the gradual adjustment mechanical. Our repeat sales methodology uses weighted least squares, and more frequent trades are weighted more heavily. An immediate response to the disaster by municipal investors would therefore also yield an immediate price response. Thus, our repeat sales approach can discern investor under-reaction from delayed observation of an immediate price reaction caused by a lack of transaction prices.

[21] The number of observations for all bonds (column 1) is lower than the sum of the observations in the REV bond (column 2) and GO bond (column 3) subsamples because some counties issue both REV bonds and GO bonds (Figure A1).

[Insert Table III here]

Panel B of Table III presents estimates of monthly cumulative abnormal returns (Equation (2)). Consistent with the weekly results (Figure II), bond prices react to natural disasters gradually and negatively over four months. The peak of the impact appears to be three months after a disaster, measuring 25 basis points for all bonds and 54 basis points for REV bonds. To alleviate a market microstructure concern that changes in bond prices can be driven by the bid–ask bounce, we repeat the weekly analysis using bond returns constructed from customer buy transactions only and obtain similar results (Table A6). We conclude that the price impacts of natural disasters on REV bonds are substantial and persist for months.

Tables B2 and B3 corroborate the results above by estimating the effects of the natural disasters in our sample on annual county-level income per capita, the unemployment rate, and tax revenue. While we find negative longer-term (five years after the disaster) impacts on unemployment, there is only a short-term decline in per-capita income and no evidence of either a short-term or long-term decline in tax revenue. The absence of a decline in tax revenue is consistent with earlier findings by Miao et al. (2018), Masiero and Santarossa (2020), and Miao et al. (2020). Tax revenues may be unaffected despite higher unemployment because a large share of local tax revenue comes from property taxes rather than taxes closely linked to local labor markets (e.g., income taxes). Overall, it appears that the typical natural disaster in our sample does not impair the typical municipal bond issuer's ability to repay general obligation bonds. The presence of some negative economic impacts may harm revenue streams specific to some revenue bonds, although we unfortunately lack data to test for such impacts directly.

C. Insured Municipal Bonds

Municipal bonds are often guaranteed by insurance that covers coupon and principal payments against default. This credit-enhancement scheme allows insured bonds to inherit bond insurers' credit ratings. The fraction of insured bonds peaked in 2005 at 57.3%, but then fell to 5.5% in 2011 following the collapse of bond insurers in the 2008 financial crisis (Lai and Zhang 2013). Municipal bond insurance became popular again after 2013: by 2016, 20% of GO bonds issued were insured (Cornaggia, Hund, and Nguyen 2019). In our whole sample, 56% of the bonds are insured overall, but this share averages only 19% in 2009 or later.

To the extent that the prices declines we find above are due to beliefs that disasters jeopardize revenue bond issuers' repayment capability, we should not expect to find price impacts among insured revenue or general obligation bonds as long as investors believe that bond insurance provides an effective guarantee against disaster risk. However, if the investor reaction is due to disasters increasing risk aversion or demand for liquidity, or if there is another behavioral channel at play, then we may find even insured bond prices declining following a natural disaster. Investor demand for liquidity may be affected because many municipal bond investors are individuals living in the broad geographic proximity of the bond issuer and may thus themselves be negatively affected by the natural disaster.

Estimates of Equation (3) using insured bonds only are shown in Table IV. We find statistically insignificant and economically small price declines for insured bonds, suggesting that the overall response is driven by a concern about repayment capability rather than increased demand for liquidity, increased risk aversion, or behavioral motives. More broadly, the contrast between insured and uninsured bond returns helps us rule out the possibility that municipal bond investors—a large share of whom are retail investors—are reacting to the natural disaster itself rather than to its financial implications.

[Insert Table IV here]

D. Implications for Climate Change

We measure ex-post bond price responses (i.e., following the occurrence of a natural disaster). We now build on these results to understand what they indicate about responses to increase in disaster risk due to climate change. Are investors reacting largely to unexpected disasters or is there reaction a simple function of disaster occurrence, regardless of ex-ante risk? To address this question, we perform two related analyses, considering how the post-disaster impact differs by (1) historic disaster damage and (2) flood risk in 2022–2052, as calculated by First Street Foundation.[22] We define county-level historic disaster damage as the average annual per-capita property and crop

[22] Available from `https://aws.amazon.com/marketplace/pp/prodview-r36lzzzjacd32?sr=0-1&ref_=beagle&applicationId=AWSMPContessa`.

damage, including years with zero total damage. We consider two versions of this risk measure - one that includes all disasters in 1960–2018 and one that is based only on disasters occurring prior to the year 2000.

First Street Foundation's flood risk database reports the share of properties in a county falling into each of ten flood risk categories. Because over 80 percent of properties fall into the lowest-risk category in the average county, we define flood risk as the share of properties in the county falling into this category and define high-risk counties as those with a below-median share of lowest-risk properties. Unfortunately, reliable projections of future risk are not readily available for most other types of natural disasters. The measure of flood risk from the First Street Foundation includes floods related to hurricanes and tropical storms, however. Combined with floods due to other causes (e.g., heavy rainfall), floods are the most common and most damaging natural disaster type faced by the US.

We find that the post-disaster price response of revenue bonds is substantially higher in counties with below-median historic disaster damage (–60 to –68 basis points), regardless of the historic risk measure used (Panels A and B of Table V). In counties with above-median historic damage, the point estimates for revenue bonds are smaller (–24 to –42 basis points) and not statistically significant, although we cannot rule out that there is a meaningful price decline for high-risk counties as well. These patterns cannot be explained by counties with lower historic damage being more likely to experience higher current disaster damage. Instead, the opposite is true: every dollar of pre-2000 per-capita damage is associated with an 81-cent increase in contemporaneous per-capita damage (conditional on such damage exceeding $3).

Panel C of Table V shows the estimated price effects when counties are split by whether they are above or below median flood risk. Cumulative revenue bond returns in low flood risk counties fall by over 66 basis points following a natural disaster, whereas high flood risk counties experience an insignificant return decrease of 24 basis points. This pattern is again not explained by lower flood risk counties experiencing more damaging disasters: conditional on experiencing a natural disaster that causes damage of at least $3 per capita, high flood risk counties experience $228 more in per-capita damage than low flood risk counties. Unsurprisingly, high flood risk counties also have higher historic damage: a county with above-median flood risk has historic damage that is about double that of a below-median flood risk county. However, over 40 percent of US counties are low-risk by one measure and high-risk by the other measure.

The measured effects in Table V are consistent with two possibilities: historically low-damage counties being less able to cope with natural disasters of a given magnitude or an updating of beliefs among investors about the likelihood of future events. Regardless of which of these two possibilities is correct, the implication is that projected increases in risk will cause repeated shocks to the municipal bond market, as many counties will experience natural disasters that are more severe and more frequent than their histories indicate.

E. The Role of Disaster Severity, Federal Disaster Aid, and Ex-Ante Mitigation Efforts

If the prices responses measured above are due to rational investors reacting to municipalities' reduced ability to repay revenue bonds, we would expect to see stronger responses to larger natural disasters. Figure III shows estimates of Equation (1) for events with below-median estimated per-capita damage (left) and above-median per-capita damage (right), focusing on uninsured bonds.[23] Price declines are substantially larger for uninsured bonds issued by counties that experience above-median damage (Panel A, Graph A2) and are driven almost entirely by REV bonds (Panel B, Graph B2). Weekly abnormal cumulative returns of uninsured REV bonds in counties with above-median damage fall by almost 0.70% within fifteen weeks of a disaster. In contrast, we find essentially no price impacts for GO bonds even for disasters of above-median severity (Panel C, Graph C2), suggesting that cash flow source diversification makes bond prices resilient to both larger and smaller natural disasters. We find no evidence of differential pre-trends in either of these subsamples.

[Insert Figure III here]

Although the focus of our analysis is physical risk, it is crucial to recognize that, in countries like the United States, the effects of natural disasters should never be viewed in isolation from policy, mainly because many severe disasters are accompanied by federal disaster aid. Policy may play a pivotal role in determining how well a municipality prepares for, responds to, and recovers from such calamities. For example, the provision of extra disaster aid money can make a significant dif-

[23] Conditional on experiencing above-median damage, the average per-capita damage is \$528 and the median is \$44.1. Below-median damage disasters involve an average per-capita damage of \$6.14 and a median per-capita damage of \$5.53.

ference for disaster-affected municipalities, enabling them to rebuild critical infrastructure, support displaced households, and implement long-term recovery plans. Measuring the extent to which disaster *response* matters for the price responses observed above is essential for understanding the mechanisms through which natural disasters create challenges for the municipal bond market.

Figure IV shows weekly price dynamics for municipal bonds issued in disaster-affected counties that (a) received no disaster aid, (b) received below-median aid per estimated dollar of damage (including no aid), and (c) received above-median aid. Counties that receive no aid comprise about 60% of the below-median aid sample. Revenue bond prices decline to a greater extent for bonds issued by counties that receive little or no post-disaster aid (Graphs A1 and A2 in Panel A). Although disaster damage in the counties that receive no aid is substantially lower than damage in counties that receive at least some aid—average per-capita damage is $54 versus $336 for the no-aid and some-aid samples, respectively—the price declines are largest for the no-aid sample (Graph A1), suggesting that financial transfers reduce the cash flow risk associated with municipal bonds in disaster-affected areas. As before, we find almost no price response among GO bonds (Figure IV, Panel B).

[Insert Figure IV here]

The damage reported by SHELDUS is a noisy measure of true damage. The measurement error, however, should bias us toward finding no heterogeneity in federal disaster aid per dollar of damage. Because greater damage tends to cause larger price drops, holding all else equal, unobserved damage would counteract any positive effects of federal disaster aid, driving the estimated price effect toward zero. Since areas with more severe damage receive more disaster aid on average, the true heterogeneity in the effects of federal disaster aid could be even larger than what we estimate.

We next use a difference-in-differences specification to concisely summarize the results shown in Figures III and IV (Panels A and B of Table VI, respectively). Post-disaster prices of uninsured REV bonds in counties that experience above-median disaster severity are 0.61% lower. In contrast, the price response of REV bonds to below-median disaster severity is approximately 40% smaller (with a point estimate of –0.35%) and statistically insignificant. Estimates for GO bonds are always small and statistically insignificant.

[Insert Table VI here]

Counties that receive zero or below-median disaster transfers experience substantial post-disaster price declines in their uninsured REV bonds of 1.20% and 0.71%, respectively (Panel B, Table VI). The economic magnitude of these estimates is substantially larger than that of the average price decline reported in Table III. By contrast, uninsured REV bonds issued by counties that receive above-median disaster aid experience (statistically insignificant) price declines of only 0.30%. Consistent with the previously reported results for GO bonds, we do not find significant bond price changes for any level of disaster aid.

Finally, we consider whether the price response varies by ex-ante mitigation efforts, splitting counties by whether reported investment in mitigation projects prior to a disaster (normalized by disaster damage) is above or below median.[24] Although these results should be viewed as suggestive because disaster damage could well be a function of pre-disaster mitigation efforts, the results, reported in Table A5, indicate that the market reaction is largest when mitigation efforts are weak. To the extent that ex-ante mitigation efforts reflect an expectation of greater disaster damage, the results are also consistent with the idea that unexpected disasters generate a larger market reaction. As before, REV bonds react more strongly than GO bonds.

Overall, the results in this section imply that federal disaster aid is very important for alleviating disaster risk to municipal bonds that are backed by undiversified revenue sources and appears to be a larger determinant of the post-disaster price response than physical damage, at least for the events in our sample. Because the final amount of federal disaster aid for any given disaster may not be known for some time following an event, our estimates may be driven by ex-ante investor expectations. These expectations could in turn be shaped by observing which assistance programs a county is declared eligible for and/or by the characteristics of the affected county (e.g., the political power of its congressional representative). We leave these more in-depth investigations for future research.

[24] Mitigation efforts are calculated as a 3-year rolling average of historical investment in disaster-mitigation projects, as reported by FEMA data, divided by the sum of contemporaneous crop and property damage.

F. Local Government Finances

Our results thus far show that returns of GO bonds are not affected by natural disaster shocks, regardless of disaster severity or federal disaster aid. A natural hypothesis is that the difference between the behavior of GO and REV bond prices reflects the fact that cash flow sources of GO bonds—overall municipal revenue—are more diversified than those of REV bonds, which are typically backed by a single project. This hypothesis implies that, if natural disasters undermine municipalities' creditworthiness, GO bonds issued by municipalities that have less room to maneuver—for example, those with high leverage—can be negatively affected by natural disasters. Additionally, because many municipalities receive a non-trivial share of their budget from state and federal governments, the cash flow sources of GO bonds are naturally more geographically diversified than those of revenue bonds. Counties that rely more heavily on local revenue are more likely to experience risky cash flows following disasters—which affect local businesses and infrastructure—than counties that take in more revenue from intergovernmental transfers, which is much more geographically diversified. This fact implies that GO bonds issued by municipalities whose budgets are largely financed by local revenue could also be vulnerable to post-disaster price declines. We now test these hypotheses.

To examine whether GO bonds experience significant price declines when their issuers' financial conditions are poor, we calculate the debt-to-tax-revenue ratio for each county in the year prior to a natural disaster using data from the Census of Governments. We define a binary variable, $Levered_c$, as equal to one if county c falls into the top tercile of the debt-to-tax ratio and zero otherwise. We then interact $Levered_c$ with the post-disaster indicator and examine the extent to which cumulative abnormal returns are more negative for highly leveraged counties. Similarly, we consider revenue to be concentrated in local sources if its local share in the pre-disaster year falls into the top tercile of the respective distribution and examine heterogeneity in post-disaster returns along this dimension. Because the impact of local financial conditions and geographic revenue diversification likely depend on disaster severity, we split the sample by whether a county experiences a very severe disaster (per-capita damage in the top tercile) or a less-severe disaster (per-capita damage in the bottom tercile).

Panel A of Table VII shows that the most severe disasters cause the prices of GO bonds issued by counties with high financial leverage to decline by 0.55% more than of those issued by low-leverage counties (column 2).This finding is consistent with our hypothesis insofar as the diversification benefit of backing bonds with tax revenue is low when counties are in poor financial standing. Financial leverage does not seem to matter, however, for returns of GO bonds issued by counties that are affected by less severe disasters (column 1). Local financial conditions are not relevant to post-disaster returns of REV bonds (columns 3–4): the estimated coefficients on the interaction term between the high leverage and post-disaster indicators are not statistically significant, regardless of disaster severity.

[Insert Table VII here]

Panel B of Table VII shows that GO bonds issued by counties whose revenue is relatively concentrated geographically are more vulnerable to natural disaster shocks and experience greater price declines: when disaster severity falls into the top tercile, the returns of GO bonds fall by an additional 0.55% among governments with high local revenue shares compared to other governments, which experience no change in GO bond returns even for these severe natural disasters. In contrast, although REV bond returns fall following both less and more severe natural disasters, the extent of their decline does not depend on local revenue source concentration (columns 3–4).

IV. Discussion and Conclusion

Although extreme weather events are by definition infrequent, they regularly cause great damage around the world. Climate change is increasing the frequency and intensity of such events, but we have yet to fully understand their implications for investors and local financing. We estimate the extent to which natural disasters—extreme meteorological events that cause extensive local damage—affect municipal bond returns. A major hurdle we face is the lack of traded prices resulting from the fact that municipal bonds trade extremely infrequently. We overcome this challenge with the repeat sales approach and estimate weekly municipal bond returns for over 900 counties in the United States, providing the first comprehensive evidence pertaining to the risk that natural disasters pose for municipal bond investors.

We document that natural disasters have significant negative impacts on municipal bond prices for counties that are hit by natural disasters. Compared with similar disaster-free counties, uninsured municipal bond returns fall on average by 0.31% in the four months following an event. Revenue (REV) bonds experience an even larger negative price impact of –0.51%, suggesting that cash flow source diversification is important for price stability in this setting. Consistent with the price response being a rational one following deterioration of bond creditworthiness, prices of insured municipal bonds are unaffected by natural disaster strikes.

Although bigger disasters cause larger price declines, federal disaster aid alleviates the negative price impacts substantially and seems to matter more than the physical damage, as we find the largest price declines in less-affected counties that subsequently do not receive disaster aid. We also find larger price declines in disaster-affected counties that have lower historic disaster risk, even though such counties experience less damage on average. This pattern suggests that there will be gradual adaptation to climate change, as investors' risk expectations adjust to actual risk.

Financial conditions in municipalities also matter, as the price of general obligation (GO) bonds issued by counties with high financial leverage declines substantially following natural disasters. Finally, geographic concentration in sources of revenue is important: counties that rely heavily on local tax revenues experience more negative returns on their GO bonds when hit by natural disasters.

While approximately 42% of municipal bonds are owned directly by households that may be relatively prone to behavioral biases, over 50% are also owned by relatively sophisticated institutional investors including mutual funds, banks, and insurance companies (Federal Reserve Board Financial Accounts of the United States, 2021). It is thus an empirical question whether investors' subjective perceptions of disaster risk or investors' rational assessment of damage incurred by disasters play a major role in driving bond prices. We do not find any evidence that biased subjective perceptions are playing a role in our setting. Overall, the patterns of heterogeneity and the relative stability of the price declines in the post-disaster period tend to be consistent with rationality.

Bharath and Cho (2021) find that experiencing a natural disaster increases individuals' risk aversion and reduces the probability that they participate in risky asset markets. Although we lack data to measure investors' risk aversion before or after a natural disaster, the patterns of results combined with the fact that many investors are households residing in or near affected areas imply that our findings may be at least partly attributable to higher risk aversion.

It is possible ex-ante that *salience* plays a key role in how municipal bond investors react to natural disasters. Ex-post, however, a simple salient story is unlikely to be the major driver of our results. It is difficult to explain why the salience of a natural disaster would affect prices of uninsured but not insured bonds or affect REV bond prices but not GO bond prices. Similarly, although greater per-capita damage is likely more salient, larger amounts of federal disaster aid per dollar of damage are not necessarily comparably salient. Likewise, the financial conditions of one's local government are not salient characteristics.

The extent to which natural disaster risk might raise future municipal bond yields depends on the extent to which municipalities mitigate this risk by shifting to GO bonds or insured bonds. If climate change causes natural disasters to be more strongly correlated and more severe, however, the effectiveness of bond insurance will also be compromised as counterparty risk in insurers will tend to increase with correlated defaults. Nevertheless, our findings imply that, absent changes in federal aid policy, municipalities will find local financing increasingly expensive in a world where natural disasters are more frequent.

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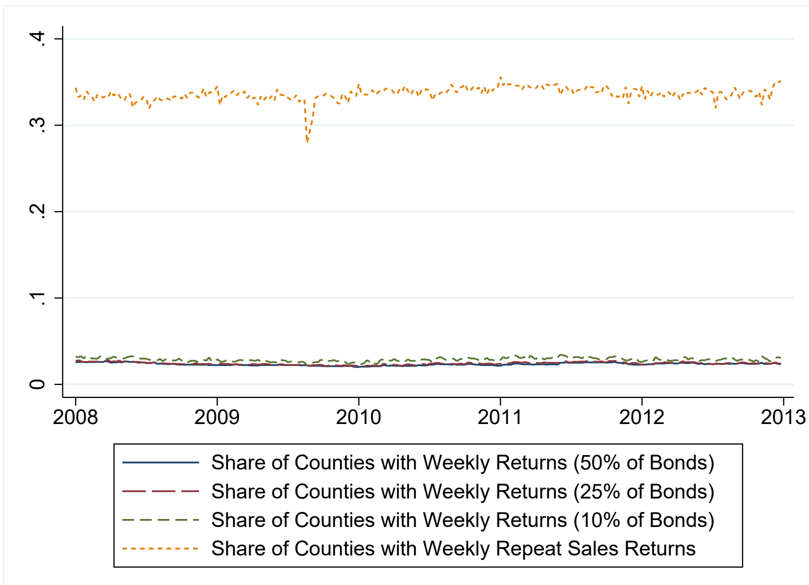
Figure I. Bond Return Availability and Transaction Frequency

The figure illustrates return data availability (Panel A) and municipal bond transaction frequency (Panel B). Panel A plots the fraction of counties with weekly bond returns. A county earns a weekly return at week t if a given percentage (50%, 25%, 10%) of outstanding bonds issued by the county earn returns at t. The denominator is the number of counties with outstanding municipal bonds at t. We also plot the share of counties with weekly repeat sales returns (the yellow dotted line), defined as the number of counties for which we can estimate weekly repeat sales returns divided by the number of counties with outstanding municipal bonds. Panel B displays the transaction frequencies of municipal bonds. "Share of Muni Bonds with Daily Transactions" is the daily share of municipal bonds with at least one transaction, averaged to the monthly level for smoothness. Weekly and monthly shares are defined similarly, using weekly and monthly shares, respectively.

Panel A: Share of Counties with Weekly Bond Returns



Panel B: Bond-level Transaction Frequency

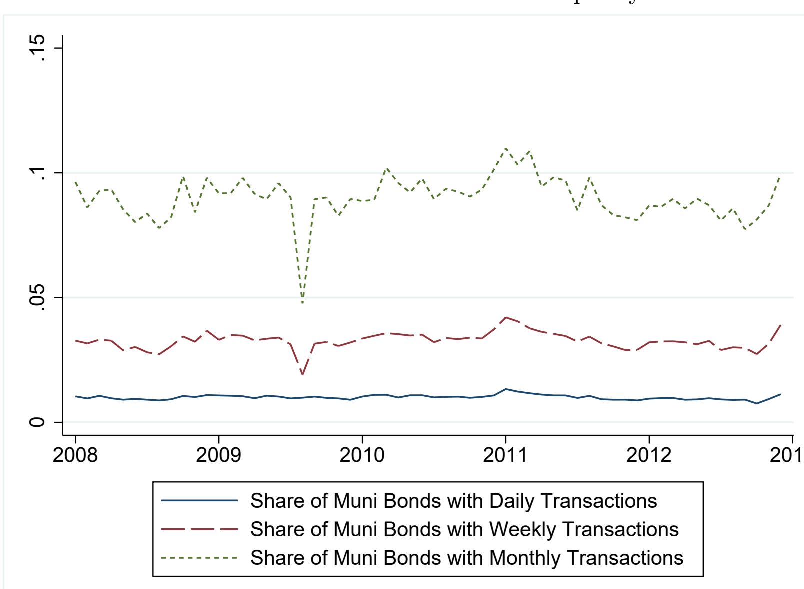
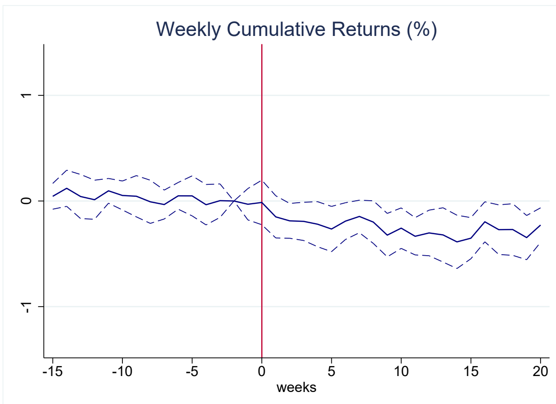


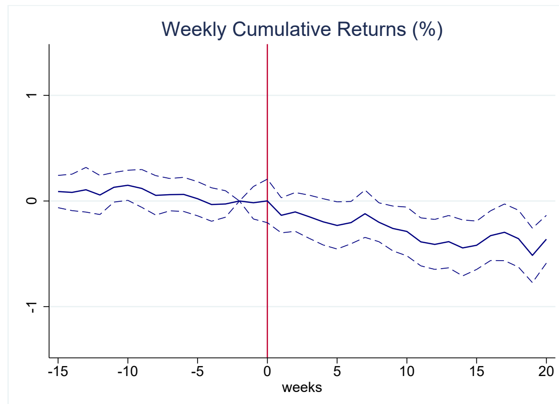
Figure II. Cumulative Abnormal Returns Around Natural Disasters: GO vs. REV Bonds

This figure plots weekly county-level cumulative abnormal returns, in percentages, of uninsured municipal bonds estimated using Eq. (1). Returns plotted in Panel A are weighted averages of GO and REV bond returns, weighted by total par value. Panels B and C include only REV or GO bonds, respectively. The solid line plots the series of estimated coefficients, and the surrounding dotted lines represent 90% confidence intervals. The red vertical line indicates the week of a disaster. All estimates are relative to two weeks prior to the disaster. All regressions include county fixed effects. Standard errors are three-way clustered by week-year, the number of weeks from the disaster, and county.

Panel A: All Bonds



Panel B: REV Bonds



Panel C: GO Bonds

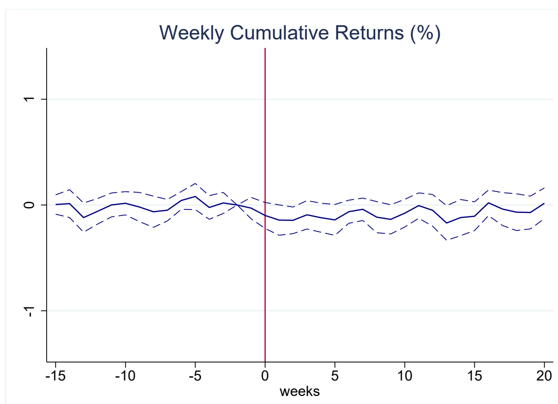
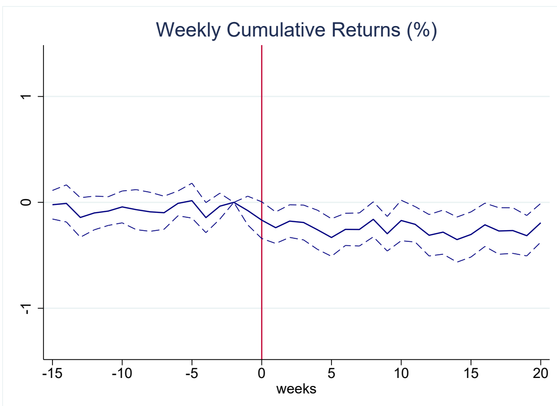


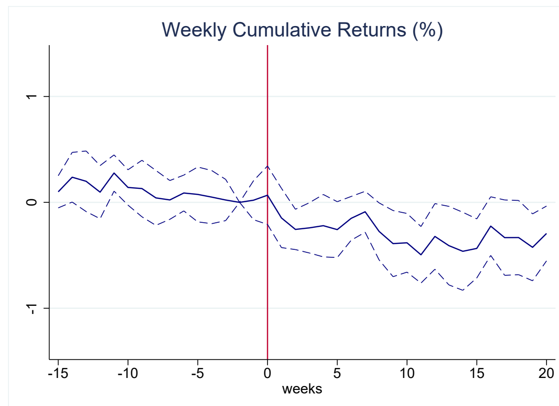
Figure III. Cumulative Abnormal Returns Around Natural Disasters: Disaster Severity

This figure plots weekly county-level cumulative abnormal returns, in percentages, of uninsured municipal bonds estimated using Eq. (1) separately for counties that experience above- and below-median damage per capita. Returns reported in Panel A are weighted averages of GO and REV bond returns, weighted by total par value. Panels B and C include only REV or GO bonds, respectively. Graphs on the left (right) include subsamples of counties below (above) the median of contemporaneous per-capita damage. The solid line plots the series of estimated coefficients, and the surrounding dotted lines represent 90% confidence intervals. The red vertical line indicates the week of a disaster. All estimates are relative to two weeks prior to the disaster. All regressions include county fixed effects. Standard errors are three-way clustered by week-year, the number of weeks from the disaster, and county.

Panel A: All Bonds

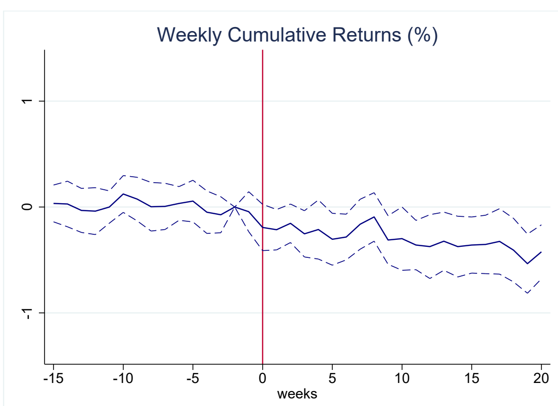


(1) Below Median Damage

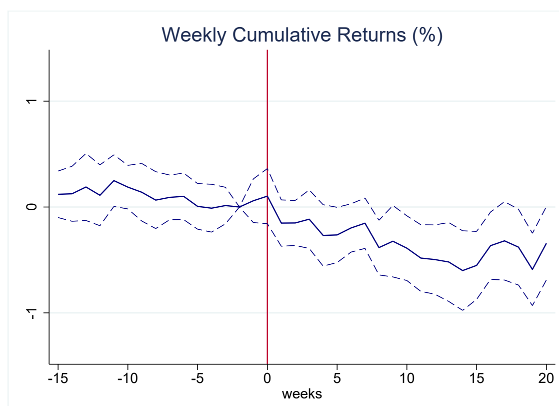


(2) Above Median Damage

Panel B: REV Bonds



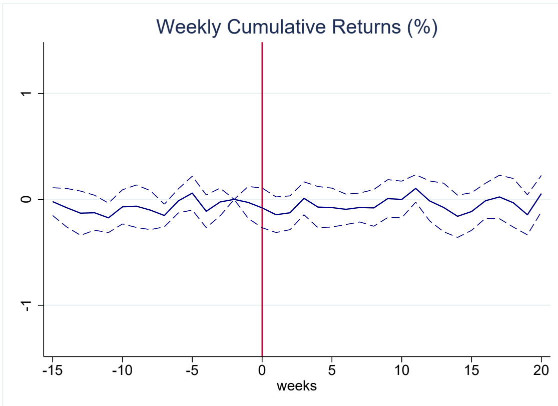
(1) Below-Median Damage



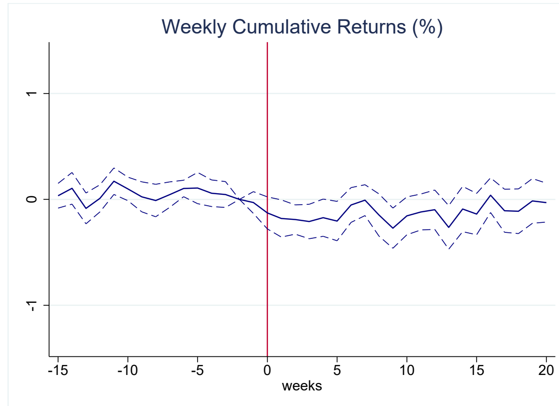
(2) Above-Median Damage

Figure III (Cont.). Cumulative Abnormal Returns Around Natural Disasters: Disaster Severity

Panel C: GO Bonds



(1) Below-Median Damage

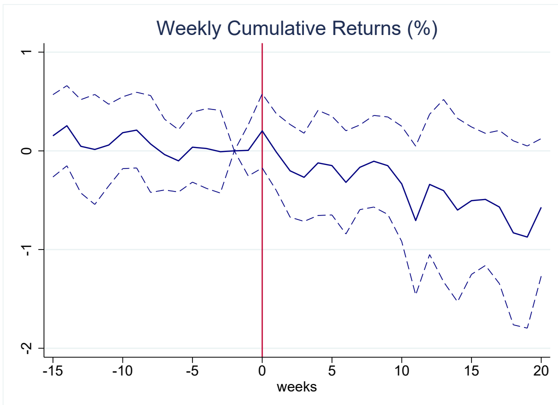


(2) Above-Median Damage

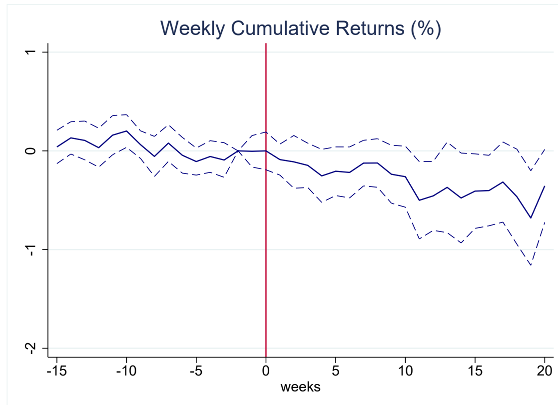
Figure IV. Cumulative Abnormal Returns Around Natural Disasters: Federal Disaster Aid

This figure plots weekly county-level cumulative abnormal returns on uninsured municipal bonds estimated using Eq. (1) separately for counties receiving zero (left), below-median (middle), and above-median (right) federal disaster aid per dollar of damage. Panels A and B plot coefficient estimates for REV and GO bonds, respectively. The solid line plots the series of estimated coefficients, and the surrounding dotted lines represent 90% confidence intervals. The red vertical line indicates the week of the disaster. All estimates are relative to two weeks prior to the disaster. All regressions include county fixed effects. Standard errors are three-way clustered by week-year, the number of weeks from the disaster, and county.

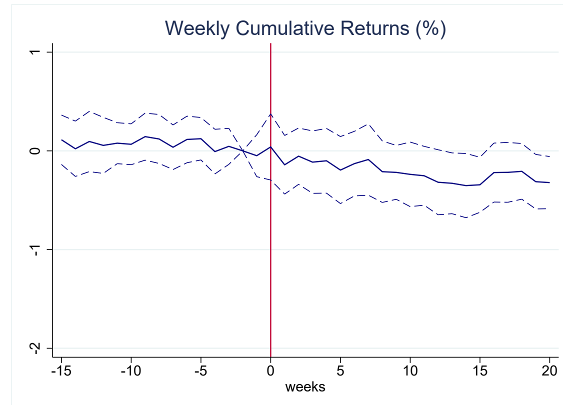
Panel A: REV Bonds



(1) Zero Federal Aid



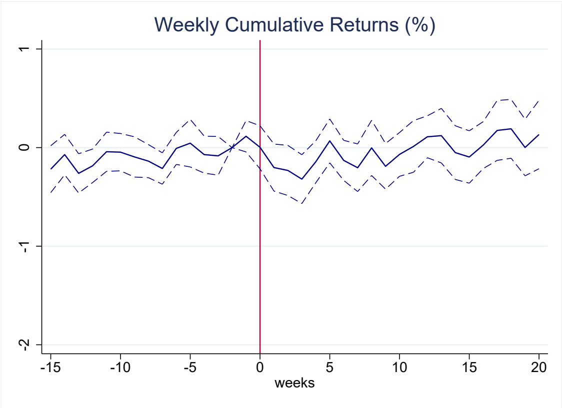
(2) Below-Median Federal Aid



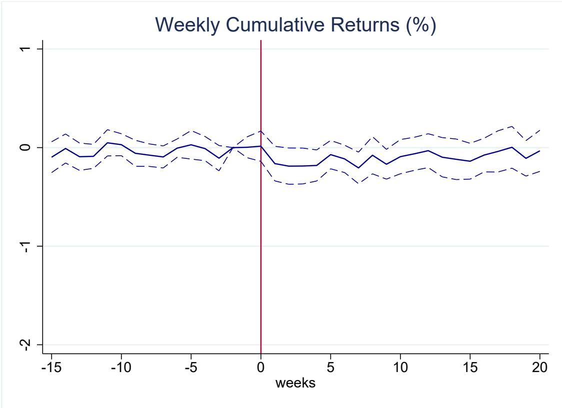
(3) Above-Median Federal Aid

Figure IV (Cont.). Cumulative Abnormal Returns Around Natural Disasters: Federal Disaster Aid

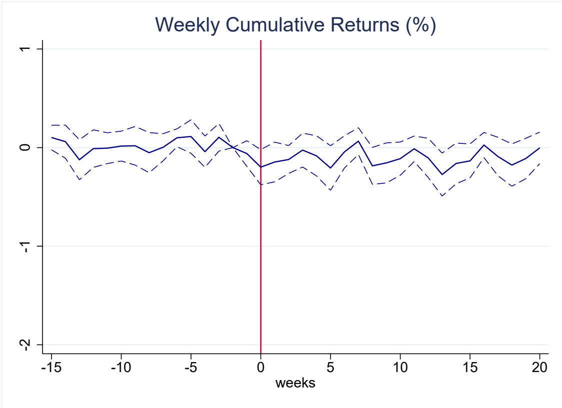
Panel B: GO Bonds



(1) No Federal Aid



(2) Below-Median Federal Aid



(3) Above-Median Federal Aid

Table I Summary Statistics

In this table we report summary statistics for weekly county-level bond returns, natural disasters, and various county characteristics from 2005 through 2018. In Panel A we report the summary statistics for weekly returns of uninsured municipal bonds, estimated using the repeat sales method. *Ret, All Bonds (%)* is the estimated return using both GO bonds and REV bonds. *Ret, REV Bonds (%)* (*Ret, GO Bonds (%)*) uses only REV (GO) bonds for the estimation. In Panel B we report the summary statistics for natural disasters that have estimated returns from repeat sales using all bonds and county characteristics. A natural disaster is defined as an event that has normalized damage greater than equal to the 75th percencile of county-level disasters in the SHELDUS data. Per-capita damage is defined as the sum of property damage and crop damage divided by the population in a county. Injuries (Fatalities) is the number of people in a county who suffered injuries (fatalities) as a result of a disaster. In Panel C we report the summary statistics for characteristics of counties with repeat sales returns and experienced natural disasters. Average county-level municipal bond characteristics are calculated using the par value of each bond at issuance as a weight. *Avg Insured GO* and *Avg Insured REV* are average proportions of outstanding insured bonds of each type. # of Bonds Outstanding is the number of outstanding municipal bonds issued by a county. Maturity is calculated in years. Ratings are converted to numerical values by assigning 1 to AAA, 2 to AA+, and so on. *Federal Aid* is total federal disaster aid. *Debt/Cash and Security* is the total debt carried by all local governments in a county divided by the total cash and securities holdings of all local governments in the county. *Debt/Tax Revenue* is the total debt of all local governments in a county divided by the total tax revenue of all local governments in the county.

Panel A: Weekly Bond Returns

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Ret, All Bonds (%)	-0.001	1.542	-34.132	-0.51	0.004	0.562	42.615	339391
Ret, REV Bonds (%)	0.002	1.894	-34.132	-0.551	0	0.609	42.615	218304
Ret, GO Bonds (%)	-0.002	1.39	-15.062	-0.509	0.008	0.571	17.321	247898

Panel B: Natural Disasters

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Injuries	2.961	27.329	0	0	0	0	720	1033
Fatalities	0.567	4.047	0	0	0	0	86	1033
Property Damage ($M)	137.1	1226	0	1.127	4	14.002	20000	1033
Crop Damage ($M)	2.553	16.5844	0	0	0	0	286	1033
Per-capita Damage ($)	269.137	2392.438	3.077	5.319	11.042	39.248	60096.34	1033

Panel C: County Characteristics

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Avg Insured GO (%)	50.47	32.78	0	19.28	50.23	80.84	100	990
Avg Insured REV (%)	56.95	30.59	0	30.26	59.57	85.28	100	1025
Avg Maturity GO	6.85	2.63	0	5.28	6.61	8.4	17.84	990
Avg Maturity REV	7.83	2.58	0	6.35	7.79	9.33	20.43	1025
Avg Rating GO	2.49	1.05	1	1.58	2.44	3.18	8.97	974
Avg Rating REV	3.59	1.3	1	2.92	3.52	4.15	9.49	1014
# of Bonds Outstanding	1181.78	1571.3	40	360	750	1367	14939	1033
Population (000s)	616.68	827.64	3.93	176.58	383.54	745.46	10040.07	1033
Income Per Cap ($K)	40.08	11.99	18.15	32.02	38.2	46.03	154.08	1033
Unemployment (%)	6.38	2.62	2	4.4	6	7.9	28.9	1033
Federal Aid ($M)	9.51	50.4	0	0.01	0.76	4.2	1159	1033
Debt/Cash and Security	1.61	0.94	0.3	1.07	1.4	1.87	9.44	1025
Debt/Tax Revenue	3.47	3.1	0.6	1.98	3.03	4.13	51.32	1025

Table II Natural Disasters and Bond Returns: Using the Conventional Approach

In this table we report estimates of Equation (3) using abnormal county-level monthly returns, in percentages, as the dependent variable. County-level monthly returns are calculated by taking averages across all bonds within the county that earn monthly returns (i.e., bond prices available in two consecutive months). We require that counties have at least two bond-month observations available to calculate county-level bond returns for the county-month. The benchmark counties are the same as those in our baseline regressions based on the repeat sales approach. The prior-disaster indicators in the same or neighboring county ($D^M_{c,t,\tau}(p)$ and $E^M_{c,t,\tau}(q)$ in Equation (3)) are not included because of the small sample size. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	Raw Returns	
	REV Bonds	GO Bonds
Post	-1.2733	-0.0127
	(-1.0952)	(-0.0015)
County FE	YES	YES
No. of Obs.	38	15
Adj. R-Squared	0.22	0.1

Table III Natural Disasters and Bond Returns: GO vs. REV Bonds

In this table we report estimates using Equation (3) in Panel A and Equation (2) in Panel B. The dependent variable is monthly cumulative abnormal returns, in percentages. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Panel A: Pre- vs. Post-Disaster Estimation

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
Post	-0.3144**	-0.5089**	-0.1277
	(-2.3279)	(-2.5602)	(-1.0594)
County FE	YES	YES	YES
No. of Obs.	1996	1185	1316
Adj. R-Squared	0.31	0.32	0.3

Panel B: Month-by-Month Estimation

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
M(-2)	0	0	0
M(-1)	-0.0391	-0.13	0.0748
	(-0.5141)	(-1.0794)	(1.1645)
M(0)	-0.0397	-0.1666	-0.0414
	(-0.4465)	(-1.5147)	(-0.4966)
M(1)	-0.0997	-0.3318**	-0.0391
	(-0.9475)	(-2.4351)	(-0.4536)
M(2)	-0.2031*	-0.3817**	-0.1196
	(-1.7785)	(-2.3219)	(-1.1282)
M(3)	-0.2470**	-0.5423***	-0.1055
	(-2.2873)	(-3.0557)	(-0.9218)
M(4)	-0.2235*	-0.4717***	-0.0251
	(-1.8391)	(-2.6482)	(-0.2220)
County FE	YES	YES	YES
No. of Obs.	6990	4150	4606
Adj. R-Squared	0.4	0.39	0.35

Table IV Natural Disasters and Bond Returns: Municipal Bond Insurance

In this table we report estimates using Equation (3) for the sample of insured municipal bonds. The dependent variable is monthly cumulative abnormal returns, in percentages. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
Post	-0.099	-0.1419	-0.06
	(-1.2862)	(-1.5319)	(-0.5195)
County FE	YES	YES	YES
No. of Obs.	3191	2052	1987
Adj. R-Squared	0.25	0.2	0.3

Table V Unexpected Disasters

In this table we report estimates of Equation (3) for subsamples split by unexpectedness of natural disasters estimated by historic damage (Panels A and B) and future flood risk (Panel C). We use two measures for the historic damage: 1) average annual per-capita damage from disasters in 2018 dollars (Panel A) and 2) average annual per-capita damage excluding events in 2000 and later (Panel B) “Below Med” and “Above Med” represent below-median and above-median subsamples based on the full-sample medians. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Panel A: By Historic Damage

	Below Med	Above Med	Below Med	Above Med
Dep Var: CR	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.6816**	-0.2407	-0.2182	-0.0335
	(-2.2128)	(-1.2804)	(-1.5814)	(-0.1797)
County FE	YES	YES	YES	YES
No. of Obs.	600	585	662	654
Adj. R-Squared	0.36	0.31	0.24	0.34

Panel B: By Pre-2000 Historic Damage

	Below Med	Above Med	Below Med	Above Med
Dep Var: CR	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.6014***	-0.4246	-0.3034**	0.0372
	(-2.6991)	(-1.5729)	(-2.1214)	(0.2171)
County FE	YES	YES	YES	YES
No. of Obs.	610	575	658	658
Adj. R-Squared	0.28	0.37	0.26	0.32

Panel C: By Projected Flood Risk

	Below Med	Above Med	Below Med	Above Med
Dep Var: CR	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.6657**	-0.2441	-0.1464	-0.0834
	(-2.5070)	(-0.9536)	(-0.8607)	(-0.5136)
County FE	YES	YES	YES	YES
No. of Obs.	743	442	886	430
Adj. R-Squared	0.33	0.27	0.3	0.35

Table VI Disaster Severity and Federal Disaster Aid

In this table we report estimates of Equation (3) for subsamples split by disaster severity (Panel A) and by federal disaster aid amounts (Panel B). "Below Med" and "Above Med" represent below-median and above-median subsamples based on the full-sample medians. The dependent variable is monthly cumulative abnormal returns. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Panel A: By Disaster Severity

	Below Med	Above Med	Below Med	Above Med
Dep Var: CR	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.3502	-0.6132*	-0.1243	-0.1986
	(-1.5429)	(-1.8343)	(-0.7799)	(-1.3201)
County FE	YES	YES	YES	YES
No. of Obs.	594	591	658	658
Adj. R-Squared	0.36	0.43	0.37	0.37

Panel B: By Federal Disaster Aid

Dep Var: CR	No Aid	Below Med	Above Med	No Aid	Below Med	Above Med
	REV Bonds	REV Bonds	REV Bonds	GO Bonds	GO Bonds	GO Bonds
Post	-1.1954*	-0.7086**	-0.2969	-0.0458	-0.2433	-0.1557
	(-1.9769)	(-2.3249)	(-1.2096)	(-0.1882)	(-1.3574)	(-1.1077)
County FE	YES	YES	YES	YES	YES	YES
No. of Obs.	242	537	648	314	560	756
Adj. R-Squared	0.29	0.34	0.37	0.44	0.45	0.29

Table VII Government Debt-to-Tax Ratios and Bond Returns Around Disasters

In this table we report estimates of Equation (3), split by disaster severity and augmented with an interaction term between the post-disaster indicator and (a) an indicator for the county falling into the top tercile of debt-to-tax-ratios or (b) an indicator for the county falling into the top tercile of the local revenue share of total revenue. Low (high) severity indicates disasters in the bottom (top) tercile of severity. The dependent variable is monthly cumulative abnormal returns, in percentages. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Panel A: By Financial Leverage

Dep Var: CR	Low Severity	High Severity	Low Severity	High Severity
	GO Bonds	GO Bonds	REV Bonds	REV Bonds
Post × Levered	-0.0548	-0.5517**	-0.0635	0.2924
	(-0.2199)	(-2.3262)	(-0.1459)	(0.6155)
Post	-0.1518	-0.0142	-0.4773*	-0.5838*
	(-0.9086)	(-0.0600)	(-1.7731)	(-1.6831)
County FE	YES	YES	YES	YES
No. of Obs.	456	398	408	379
Adj. R-Squared	0.41	0.53	0.46	0.5

Panel B: By Share of Local Revenue

Dep Var: CR	Low Severity	High Severity	Low Severity	High Severity
	GO Bonds	GO Bonds	REV Bonds	REV Bonds
Post×Concentrated	0.2266	-0.5454*	0.2388	-0.01
	(0.7484)	(-1.9232)	(0.3992)	(-0.0176)
Post	-0.3643	-0.0652	-0.4649	-0.8143
	(-1.3679)	(-0.2497)	(-0.8535)	(-1.2748)
County FE	YES	YES	YES	YES
No. of Obs.	276	262	238	220
Adj. R-Squared	0.52	0.49	0.5	0.58

Appendix

Figure A1. Geographic Distribution of Counties that Issue Uninsured GO and REV Bonds

This figure shows the geographic distribution of counties that have experienced natural disasters and have issued GO bonds and REV bonds at least once during the sample period. Counties in blue have issued both GO bonds and REV bonds. Red (yellow) indicates counties that have issued only GO (REV) bonds.

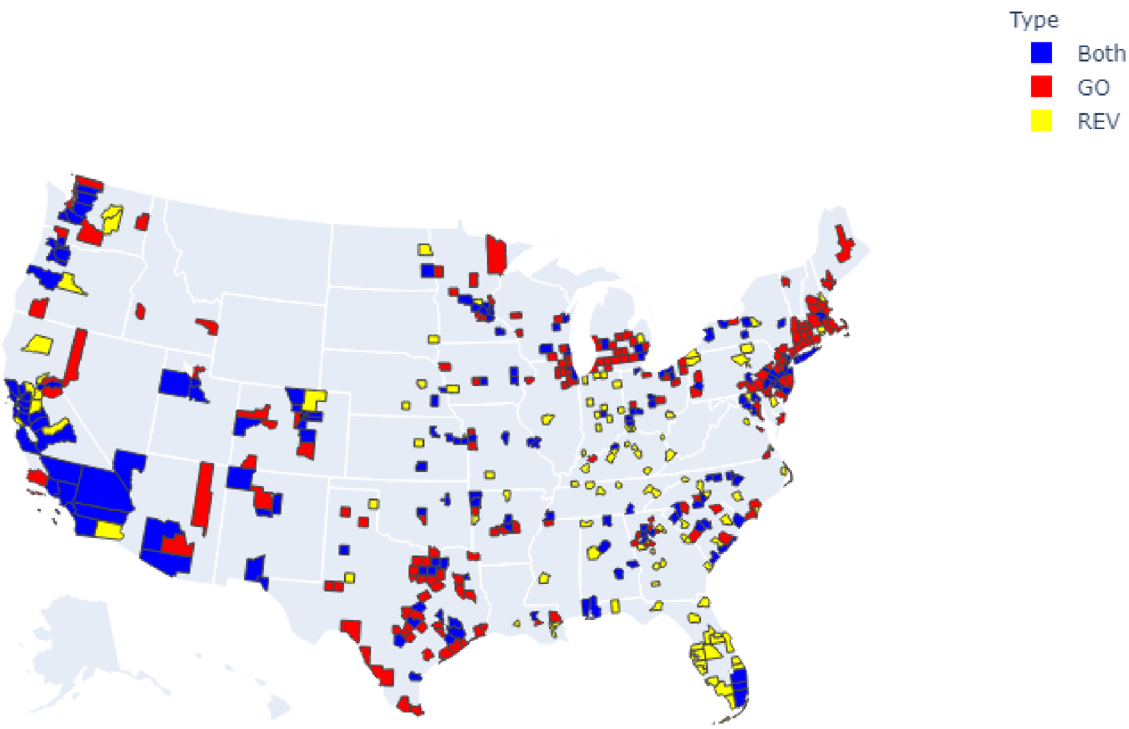


Table A1 Repeat Sales Estimation - All Bonds

In this table we report summary statistics for the number of counties for which our repeat-sales approach can be implemented and county-level weekly returns estimated using repeat sales on all bonds (both insured and uninsured) from 2005 to 2018. Panel A lists the number of counties that have sufficient return observations to implement the repeat sales methodology for each year. Column 1 lists the number of counties that have returns estimated by repeat sales using both GO and REV bonds. Columns 2 and 3 list the number of counties with repeat sales estimations using REV bonds and GO bonds, respectively. In Panel B we report the summary statistics for weekly returns of municipal bonds, estimated using the repeat sales method.

Panel A: Number of Counties Estimated by Year

	# of Counties		
Year	All Bonds	REV Bonds	GO Bonds
2005	649	383	460
2006	814	502	577
2007	815	505	579
2008	784	498	551
2009	786	503	547
2010	796	502	566
2011	804	511	580
2012	795	502	576
2013	747	483	536
2014	680	443	484
2015	615	398	429
2016	560	351	370
2017	499	309	325
2018	431	263	286
All Years	920	604	667

Panel B: Repeat Sales Weekly Returns

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Ret, All Bonds (%)	0.068	1.661	-16.893	-0.475	0.063	0.684	20.247	315119
Ret, REV Bonds (%)	0.078	2.034	-23.679	-0.52	0.06	0.737	32.678	179499
Ret, GO Bonds (%)	0.065	1.472	-12.743	-0.473	0.065	0.685	13.312	212424

Table A2 Municipal Bond Returns Around Natural Disasters: Insured Bonds

In this table we report estimates using Equation (2). The dependent variable is monthly cumulative abnormal returns of insured municipal bonds. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
M(-2)	0	0	0
M(-1)	-0.0441	-0.0313	-0.0108
	(-0.7621)	(-0.3498)	(-0.1825)
M(0)	-0.0804	-0.0429	-0.0414
	(-1.3715)	(-0.4529)	(-0.7594)
M(1)	-0.0924	-0.0964	-0.0521
	(-1.4865)	(-0.9728)	(-0.7258)
M(2)	-0.0627	-0.0208	-0.0679
	(-0.9802)	(-0.2120)	(-0.8093)
M(3)	-0.1214**	-0.1411	-0.1500**
	(-2.0565)	(-1.2651)	(-2.1514)
M(4)	-0.1255*	-0.1314	-0.099
	(-1.7382)	(-1.0962)	(-1.2988)
County FE	YES	YES	YES
No. of Obs.	11179	6956	7191
Adj. R-Squared	0.33	0.39	0.28

Table A3 Municipal Bond Returns Around Natural Disasters: FEMA Transfers and Severity

In this table we report estimates of Equation (2) by disaster severity (columns 1–4) and by federal disaster aid amounts (columns 5–8). The dependent variable is monthly cumulative abnormal returns. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	Severity				FEMA Transfer			
	Below Median	Above Med	Below Med	Above Med	Below Med	Above Med	Below Med	Above Med
	REV Bonds	REV Bonds	GO Bonds	GO Bonds	REV Bonds	REV Bonds	GO Bonds	GO Bonds
M(-2)	0	0	0	0	0	0	0	0
M(-1)	-0.0731	-0.1648	0.0106	0.1472	-0.1774	-0.0961	0.0677	0.0644
	(-0.5822)	(-1.0885)	(0.1441)	(1.5930)	(-1.4175)	(-0.7713)	(0.6861)	(0.7720)
M(0)	-0.1849	-0.1281	0.002	-0.0917	-0.1826	-0.1857	0.0678	-0.1367
	(-1.5467)	(-0.7815)	(0.0256)	(-0.8250)	(-1.5576)	(-1.0565)	(0.5537)	(-1.1678)
M(1)	-0.2932*	-0.4468**	0.0126	-0.1236	-0.3836**	-0.2431	-0.063	-0.0626
	(-1.9385)	(-2.0901)	(0.1245)	(-0.9625)	(-2.1181)	(-1.5380)	(-0.4679)	(-0.6799)
M(2)	-0.2983**	-0.5227*	-0.0787	-0.1806	-0.3140*	-0.3820**	-0.1068	-0.1867
	(-2.0578)	(-1.8764)	(-0.5917)	(-1.3820)	(-1.6796)	(-2.2007)	(-0.7934)	(-1.5158)
M(3)	-0.3336**	-0.7603***	0.0253	-0.2605*	-0.5842**	-0.4535**	-0.0636	-0.2081
	(-2.1227)	(-2.6562)	(0.1756)	(-1.7239)	(-2.2385)	(-2.2568)	(-0.4069)	(-1.5774)
M(4)	-0.3344*	-0.5638*	0.0264	-0.0712	-0.6208**	-0.2884	-0.0229	-0.1061
	(-1.8815)	(-1.9467)	(0.1885)	(-0.5023)	(-2.5635)	(-1.4383)	(-0.1559)	(-0.7840)
County FE	YES	YES	YES	YES	YES	YES	YES	YES
No. of Obs.	2198	1952	2471	2135	1877	2273	1960	2646
Adj. R-Squared	0.48	0.55	0.45	0.45	0.44	0.47	0.52	0.37

Table A4 Local Revenue Composition Summary Statistics

In this table we report summary statistics for the share of each local government revenue source. For Panel A, county-year local government revenue is classified as coming from own (local) sources, intergovernmental (IG) revenue as coming from the federal government, and IG revenue as coming from the state government. We then report the fraction of each revenue source, denoted as *% Own Sources*, *% IG Revenue Federal* and *% IG Revenue State*, respectively. *Concentrated* is an indicator that equals 1 (equals 0) if a county is at the highest (lowest) tercile of Hirfindahl-Hirchman index calculated using weights of these three revenue sources. In Panel B, we present summary statistics for the fraction of each local tax type.

Panel A: Intergovernmental Revenue Sources Summary Statistics

Type	Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Concentrated=0	% Own Sources	51.57	9.9	9.77	46.98	53.31	57.94	76.27	355
	% IG Revenue Federal	3.73	2.87	0	1.74	3.15	5.11	22.25	355
	% IG Revenue State	44.7	10.25	19.57	37.96	42.63	49.39	88.33	355
Concentrated=1	% Own Sources	77.78	5.91	60.25	73.56	77.41	81.76	97.33	314
	% IG Revenue Federal	2.52	2.2	0.01	0.88	1.99	3.44	13.44	314
	% IG Revenue State	19.7	6.13	2.31	15.81	20.03	23.54	39.58	314

Panel B: Tax Sources Summary Statistics

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Property Tax	59.61	40.34	0	0	74.13	97.93	100	1594
Total General Sales Taxes	10.23	19.75	0	0	0.13	13.92	100	1594
Alcoholic Beverage Sales Tax	0.73	8.28	0	0	0	0	100	1594
Amusement Tax	0.33	5.59	0	0	0	0	100	1594
Insurance Premium Tax	0.48	6.15	0	0	0	0	100	1594
Motor Fuels Sales Tax	0.45	6.14	0	0	0	0	100	1594
Parimutuels Tax	0	0.04	0	0	0	0	1.25	1594
Public Utilities Tax	3.82	16.54	0	0	0	1.41	100	1594
Tobacco Sales Tax	0.2	4.34	0	0	0	0	100	1594
Other Selective Sales Taxes	3.93	18.03	0	0	0	0.84	100	1594
Alcoholic Beverage License Tax	1.27	11.13	0	0	0	0	100	1594
Amusement License Tax	0.38	6.13	0	0	0	0	100	1594
Corporation License Tax	0	0.04	0	0	0	0	0.92	1594
Hunting & Fishing License	0	0	0	0	0	0	0	1594
Motor Vehicle License	1.5	11.4	0	0	0	0	100	1594
Motor Vehicle Operators Lic	0.06	2.5	0	0	0	0	100	1594
Public Utility License Tax	0.29	5.01	0	0	0	0	100	1594
Occup & Business License, NEC	4.14	18.99	0	0	0	0.37	100	1594
Other License Tax	6.04	22.48	0	0	0.16	1.14	100	1594
Indiv Income Tax	1.82	9.1	0	0	0	0	100	1594
Corporation Net Income Tax	0.14	3.55	0	0	0	0	100	1594
Death & Gift Tax	0.08	2.51	0	0	0	0	100	1594
Documentary & Stock Trans Tax	1.17	9.99	0	0	0	0	100	1594
Severance Tax	0.26	5.01	0	0	0	0	100	1594
Taxes, NEC	3.06	16.21	0	0	0	0.04	100	1594

Table A5 Natural Disasters and Cumulative Bond Returns: Disaster-Mitigation Efforts

In this table we report estimates of Equation (3) for subsamples split by ex-ante mitigation efforts. The dependent variable is monthly cumulative abnormal returns. The ex-ante mitigation efforts are calculated as the 3-year rolling-window averages of historical investments in disaster mitigation projects divided by the sum of contemporaneous crop damage and property damage. We split the sample into below-median and above-median mitigation subsamples. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

	Below Med	Above Med	Below Med	Above Med
Dep Var: CR	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.9266*	-0.5876**	-0.1148	-0.1718
	(-1.6846)	(-2.3541)	(-0.4500)	(-1.1581)
County FE	YES	YES	YES	YES
No. of Obs.	310	450	344	462
Adj. R-Squared	0.45	0.17	0.47	0.39

Table A6 Natural Disasters and Bond Returns: Using Customer Purchase Trades Only

In this table we report estimates using Equation (3) when county-level bond returns are constructed using only customer buy transactions. The dependent variable is monthly cumulative abnormal returns, in percentages, estimated using only customer purchase trades. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
Post	-0.5850**	-0.7439**	-0.1691
	(-2.5134)	(-2.2112)	(-1.2705)
County FE	YES	YES	YES
No. of Obs.	1494	1095	1105
Adj. R-Squared	0.24	0.24	0.27

Table A7 Excluding Trades Around the First Call Date

In this table we report estimates using Equation (3). The dependent variable is monthly cumulative abnormal returns, in percentages, estimated from transactions that occurred prior to the week before the first call week or after the first call week. Standard errors are two-way clustered by county and by year-month. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var: CR	All Bonds	REV Bonds	GO Bonds
Post	-0.4489***	-0.5109**	-0.2059*
	(-3.3015)	(-2.4855)	(-1.6606)
County FE	YES	YES	YES
No. of Obs.	1499	1101	1110
Adj. R-Squared	0.36	0.32	0.3

Table B1 Volatility

In this table we report estimates of Equation (3) replacing cumulative abnormal returns with volatility. The pre-event (post-event) volatility is estimated using 20 weeks window before (after) the event, and the volatility of benchmark returns is subtracted. The volatility is annualized. Panel A presents the results by REV bonds (Column 1) and GO bonds (Column 2). We further show the results for subsamples split by disaster severity (Panel B), and by federal disaster aid amounts (Panel C). "Below Med" and "Above Med" represent below-median and above-median subsamples based on the full-sample medians. The set of controls $\{D^M_{c,t,\tau}(p), E^M_{c,t,\tau}(q)\}$ are not included in this specification. Standard errors are two-way clustered by county and by year-month. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Panel A: GO and REV Bonds

Dep Var: Vol	REV Bonds	GO Bonds
Post	0.4675	0.2480
	(1.4313)	(1.1338)
County FE	YES	YES
No. of Obs.	1176	1328
Adj. R-Squared	0.31	0.32

Panel B: By Disaster Severity

	Below Med	Above Med	Below Med	Above Med
Dep Var: Vol	REV Bonds	REV Bonds	GO Bonds	GO Bonds
Post	-0.0309	1.0271*	0.1634	0.344
	(-0.0956)	(1.9457)	(0.6760)	(0.9570)
County FE	YES	YES	YES	YES
No. of Obs.	622	554	706	622
Adj. R-Squared	0.40	0.27	0.45	0.36

Panel C: By Federal Disaster Aid

Dep Var: CR	No Aid	Below Med	Above Med	No Aid	Below Med	Above Med
	REV Bonds	REV Bonds	REV Bonds	GO Bonds	GO Bonds	GO Bonds
Post	1.1040*	0.9098**	0.0868	0.9905**	0.4232	0.1217
	(1.8236)	(1.9902)	(0.2003)	(2.5738)	(1.6248)	(0.4181)
County FE	YES	YES	YES	YES	YES	YES
No. of Obs.	236	544	632	308	556	772
Adj. R-Squared	0.18	0.29	0.34	0.23	0.27	0.42

Table B2 Income per Capita, Unemployment, and Tax Revenue

In this table we report estimates of Panel regression regressing income per capita, unemployment, and tax revenue on event indicator. The panel is at county-year level. *Current* is an indicator for the county-year that had a disaster; *Short-term* is an indicator for county-year that had a disaster in last 1-2 years; *Long-term* is an indicator for county-year that had a disaster in last 3-5 years. Standard errors are clustered by county. *t*-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

Dep Var:	Income per Capita	Unemployment	Tax Revenue
Current	-1394.4858***	-0.0826	-0.0047
	(-6.2512)	(-1.4271)	(-0.1986)
Short-term	356.0371	0.0655	-0.0235
	(1.4267)	(1.0350)	(-0.9895)
Long-term	836.3147***	0.1311**	0.0468
	(3.3395)	(2.0213)	(1.1444)
County FE	YES	YES	YES
Year FE	YES	YES	YES
No. of Obs.	7809	7851	2275
Adj. R-Squared	0.93	0.87	0.98

Table B3 Income per Capita, Unemployment, and Tax Revenue

In this table we report estimates of Panel regression regressing income per capita, unemployment, and tax revenue on event indicator. The panel is at county-year level. *Current* is an indicator for the county-year that had a disaster; *Year Y* is an indicator for county-year that had a disaster in last Y years. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

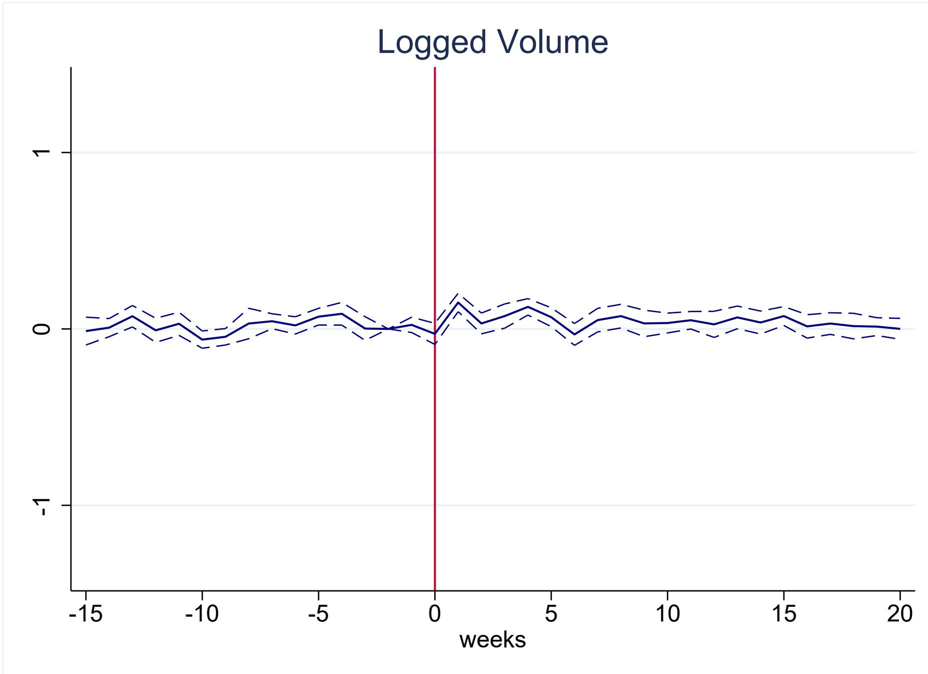
Dep Var:	Income per Capita	Unemployment	Tax Revenue
Current	-1304.3857***	-0.0409	-0.0043
	(-6.2604)	(-0.6900)	(-0.1769)
Year 1	-20.8725	0	-0.0319
	(-0.1105)	(0.0006)	(-1.4779)
Year 2	408.1013**	0.1393***	0.0515***
	(2.0409)	(2.8658)	(2.6693)
Year 3	503.8024**	0.0808*	0.0314
	(2.5007)	(1.7058)	(0.8984)
Year 4	318.6408	0.0433	-0.0121
	(1.4829)	(0.8523)	(-0.2602)
Year 5	512.6488	0.1407**	-0.0416
	(1.3744)	(2.2370)	(-0.7353)
County FE	YES	YES	YES
Year FE	YES	YES	YES
No. of Obs.	7809	7851	2275
Adj. R-Squared	0.93	0.87	0.98

Table B4 Summary Statistics (County-Year with and without Estimated Repeat Sales Returns)

Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
County-Year without Repeat Sales Returns								
Avg Insured GO (%)	62.48	39.51	0	22.26	78.95	100	100	22679
Avg Insured REV (%)	65.29	39.94	0	25	87.08	100	100	19887
Avg Maturity GO	4.78	4.11	0	1.22	4.36	7.22	30	22679
Avg Maturity REV	5.54	4.52	0	1.68	5.29	8.24	35	19887
Avg Rating GO	3.05	1.36	1	2	3	3.94	12	17914
Avg Rating REV	4.02	1.7	1	3	4	4.99	15	15457
Population (000s)	74.51	98.45	0.78	20.2	39.8	86.29	992.27	26700
Income Per Cap ($K)	33.5	10.64	12.11	26.21	31.85	38.71	161.94	26700
Unemployment (%)	6.44	2.84	1.1	4.3	5.8	8	26.3	26903
Federal Aid ($M)	1.65	28.03	0	0	0	0.25	3120	28486
Debt/Cash and Security	1.67	5.6	0	0.84	1.24	1.82	750.47	24986
Debt/Tax Revenue	3.44	9.96	0	1.34	2.11	3.34	462.11	24914
County-Year with Repeat Sales Returns								
Avg Insured GO (%)	45.1	31.56	0	15.35	43.35	72.31	100	2951
Avg Insured REV (%)	52.97	30.97	0	26.47	53.64	80.23	100	3000
Avg Maturity GO	6.08	2.57	0	4.43	6.2	7.71	17.84	2951
Avg Maturity REV	7.15	2.69	0	5.56	7.33	8.83	20.43	3000
Avg Rating GO	2.42	0.95	1	1.64	2.33	3.11	6	2887
Avg Rating REV	3.38	1.13	1	2.74	3.37	4	11	2964
Population (000s)	814.68	991.11	25.88	312.23	597.33	920.69	10105.71	2806
Income Per Cap ($K)	44.45	16.94	14.02	33.18	41.2	51.47	202.38	2806
Unemployment (%)	5.85	2.71	2	4	5.1	7.1	28.9	2849
Federal Aid ($M)	10.13	99.9	0	0	0.33	2.79	4266	3020
Debt/Cash and Security	1.63	0.97	0.1	1.11	1.45	1.9	19.57	2667
Debt/Tax Revenue	3.6	3.5	0.07	2.02	3.11	4.13	47.22	2666

Figure B1. Logged Volume of REV Bonds and GO Bonds

Panel A: REV Bonds



Panel B: GO Bonds