

Natural Disasters and Municipal Bonds*

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ABSTRACT

Climate change is increasing the frequency of extreme weather events and natural disasters, which could in turn make municipal bonds—a \$4 trillion market in the US—a riskier asset class. We study the effect of natural disasters on municipal bond returns, exploiting the repeat sales approach to overcome the challenge that municipal bonds trade extremely infrequently. Natural disasters have substantial price and volatility effects: the average return of uninsured bonds issued by disaster-affected counties falls by -0.31% , starting in the month of the disaster, translating into investor losses of over \$10 billion across all counties in our sample. The negative price effect is more than twice as large for revenue bonds and in most cases non-existent for general-obligation bonds, suggesting that revenue diversification plays a key role in bond price stability. Finally, we show that bond insurance, disaster severity, federal disaster aid, and local financial conditions each play an important role in whether price effects materialize and how large they are.

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

JEL classification: G10, G14, Q54

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Extreme weather events are becoming more frequent and more severe (Intergovernmental Panel on Climate Change, 2021). In 1990–2020, the number of disaster and emergency declarations in the US 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 with climate change. A recent survey of academics, finance professionals, and regulators revealed that physical risk ranks as the top climate-related risk for firms and investors over the next 30 years (Stroebel and Wurgler, 2021). There is also a widespread belief that asset prices underestimate climate risks. Yet studies of how physical risk is priced into asset markets have largely focused on slow-moving risks like sea level rise or on stock prices of companies whose operations are geographically scattered, in which case the effects of regional shocks may be muted and statistical power to detect such effects will be low.

We study the US municipal bond market—valued at \$4 trillion in 2021 and growing rapidly—to provide comprehensive evidence on when and how natural disasters affect municipal bond returns. Given municipal bonds’ crucial role in public financing and investment, understanding this relationship is of paramount importance for investors, municipal bond issuers, and fiscal policymakers. It is ex-ante unclear how natural disasters affect municipal bond markets, for four key reasons. First, despite being a clear 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, Kawano, and Levitt, 2018). Second, economic impacts may not correspond to changes in outcomes that are relevant for municipal bonds (e.g., tax revenue). Third, post-disaster aid may counteract the economic shock of the disaster. Finally, bond insurance may make insured municipal bonds immune to such shocks.

Combining county-level weekly bond returns with data on over 2,000 extreme weather events that happened in 2005–2018 and caused at least one dollar of real damage per capita, we use event study and difference-in-differences methodologies to estimate 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. Our novel use of this method in the municipal bond market enables us to

¹Sources: 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 in 2018 dollars.

examine *ex-post* returns immediately following disasters, which is crucial for understanding how physical climate risk—as opposed to regulatory and transitional climate risks—is priced *ex-ante* in financial markets.

Among uninsured municipal bonds, we find that natural disasters substantially decrease returns for at least 20 weeks following the event. The average decline in returns is 31 basis points over the post-event period. The overall 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 negative 51 basis points following a natural disaster. By 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 stability of bond returns heavily depends on revenue diversification. Monthly-level estimates yield very similar insights.

The magnitude of the average effect translates into investor losses of \$9.25 million per disaster-affected county or \$9.6 billion across all disaster-affected counties in our bond sample.² Per-county investor loss is more than half in magnitude to the estimated physical damage, which averages \$19.1 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.

We then investigate how bond insurance, disaster severity, and federal disaster aid affect the post-disaster trajectory of municipal bond returns. There is no significant post-disaster decline in returns of insured bonds, implying that market participants believe that insurance makes bond cash flows largely immune to natural disasters. 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 negative price impact occurs mostly among uninsured municipal bonds of counties that received little or no federal disaster aid: uninsured REV bonds in counties that receive no disaster aid experience a 1.2% post-disaster drop in returns, while uninsured REV bonds in counties with above-median disaster aid per dollar of damage experience

²The dollar value estimation is based on the par value of uninsured revenue bonds.

an insignificant post-disaster drop of 30 basis points. Among counties that receive below-median disaster aid per dollar of damage (including no-aid counties), uninsured REV bond returns fall by 70 basis points. These price responses are consistent with some combination of investors reacting to increases in municipal bonds' risk and of increases in 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 are in the highest debt-to-tax-revenue ratio quintile experience 55 basis points post-disaster decline in uninsured GO bond returns following a disaster that is in the top quintile of per-capita damage. Geographic diversification in revenue sources also plays an important role in bond price stability. Uninsured GO bonds issued by municipalities whose revenues depend relatively more on local sources (versus on transfers from state or federal governments) exhibit substantial post-disaster price declines of approximately 0.55%. 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 whose financial condition is weak. The most likely reason for this exception is that it is harder for municipalities with high debt burdens to diversify away the shock created by very severe natural disasters.

Our paper contributes to the growing literature that studies how climate change affects financial markets.³ The vast majority of this research does not consider the municipal bond market. Instead, researchers have demonstrated that natural disasters and climate risk exposure have real effects at the firm level (Leiter, Oberhofer, and Raschky, 2009; Li, Shan, Tang, and Yao, 2021; Tubaldi, 2021) and regulation and transition risks, as opposed to physical risk, of climate change have begun to matter in the financial markets (Bolton and Kacperczyk, forthcoming; Krueger, Sautner, and Starks, 2020; Seltzer, Starks, and Zhu, 2020; Hsu, Li, and Tsou, 2020; Ilhan, Sautner, and Vilkov, 2021). But Faccini, Matin, and Skiadopoulos (2021) analyze climate-change related news and conclude that physical climate risk, including natural disaster risk, is not priced in US stocks and Kruttli, Roth Tran, and Watugala (2021) also show that the options market underprices the

³See Hong, Karolyi, and Scheinkman (2020), Furukawa, Ichiue, and Shiraki (2020), and Giglio, Kelly, and Stroebel (forthcoming) for a review.

variance risk premium associated with hurricane-induced uncertainty. The disconnect between the two sets of findings could be due to different levels of aggregation—stock prices aggregate cash flows from firms’ operations across dispersed geographical regions—and underscores the importance of explicitly linking financial assets to the extreme weather events affecting them, for a sharper test of their price responses.⁴

Of the few papers we are aware of that study how climate change affects the municipal bond market, ours provides the first analysis on secondary market returns. Our study is complementary to Painter (2020) and Goldsmith-Pinkham, Gustafson, Lewis, and Schwert (2021), who examine the local effects of sea level rise (SLR) and find that long-term municipal bonds facing higher SLR risk have higher yields. SLR is a slow-moving phenomenon that may not be salient to investors,⁵ potentially eliciting different responses than natural disasters, which are salient phenomena that can affect risk perception of investors immediately (Dessaint and Matray 2017). SLR risk also affects a smaller set of communities and is easier to quantify for any given location than natural disaster risk. Additionally, Painter (2020) and Goldsmith-Pinkham et al. (2021) study either primary market or secondary market *yields*, while we examine the effect of climate changes on *returns*. As such, our results speak directly to the portfolio performance and wealth of bond investors. Moreover, we show ex-post return variation that can be priced ex-ante in bond prices, thus providing an important missing economic link as to how climate risk is priced in ex-ante bond yields.⁶

The study most closely related to ours is Jerch, Kahn, and Lin (2020), who use annual data to show that US hurricane strikes lower municipal debt ratings in the longer run. Besides considering a much larger set of natural disasters, our study builds on Jerch et al. (2020) in at least three other important ways. First, bond ratings are generally very coarse, slow to adjust to new information, and could be affected by non-price factors.⁷ By contrast, bond prices reflect timely, continuous variation in investor wealth. Second, our analysis provides comprehensive evidence on how revenue

⁴Strobl (2011) and Jerch, Kahn, and Lin (2021) demonstrate the importance of spatial disaggregation when considering economic impacts of natural disasters more generally.

⁵For 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.

⁶Several recent papers focus on the real estate market, 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.

⁷See, 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.

diversification, bond insurance, disaster severity, and external transfers matter for post-disaster bond returns are related with the negative shock by natural disasters in terms of municipal bond returns. Finally, we hold the sample of bonds fixed, whereas Jerch et al. (2020) compare bonds issued before versus after a hurricane strike. Their conclusions could therefore be affected by selection into which municipalities issue bonds in the aftermath of a hurricane. For example, if municipalities that, all else equal, receive less post-disaster aid (and are thus in worse financial shape) are more likely to issue bonds to make up for the lower funding amount, then the estimated rating impacts will be too large.

Finally, we also contribute to the debate of whether asset markets are underreacting 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 overreact to the occurrence of extreme events, but Kruttli et al. (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 overreactions. Our findings suggest that municipal bond investors—many of whom are households—are reacting consistently to natural disasters, for two reasons. First, investor reactions are largely limited to cases where the municipal bonds are uninsured and backed by revenues tied to specific projects and where the county receives less federal disaster aid than expected given disaster severity. Second, the reaction is stable and does not reverse itself for at least six months following the extreme event. Investor responses, however, exhibit a pattern of underreaction: upon a disaster, it takes more than 10 weeks for bond prices to fully reflect the shock.

I. Data

A. *Municipal Bond Data*

We use municipal bond transaction data from the MSRB 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 the trade. Because our

smallest unit of time is a week, we convert transaction-level data to weekly-level data. To do so, we first follow Bessembinder, Kahle, Maxwell, and Xu (2009) to calculate volume-weighted price averages and derive daily bond prices 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 one month after issuance. We also assume that the maturity price of bonds is their par value.

We obtain data on other bond characteristics and terms and conditions are from the Mergent Municipal Bond Database. The 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 (tax-exempt or not). The database covers municipal bonds issued between July 1960 and March 2016. We only consider tax-exempt bonds (*tax_code_c*="EXMP") with fixed or zero coupons (*coupon_code_c* equal to "FXD", "OID", "OIP", or "ZER").⁸ 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 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 versus uninsured based on the *bond insurance code* in Mergent.⁹ We drop bonds that do not pay semi-annual coupon 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 only includes bonds issued before that date. However, the MSRB data allow us to track bond prices up to June of 2020. Our final sample includes 709,608 bonds issued by 2,223 counties, with price data spanning January 2005 to June 2020.

⁸While original-issued discount (OID) and original-issued premium (OIP) bonds do not necessarily pay fixed coupon, 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 more details on why OIP bonds are commonly used in the municipal bond market.

⁹We classify a bond as insured if *bond_insurance_code* is not missing and as uninsured if *bond_insurance_code* is missing.

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 information on county-level employment, personal income, and population. We supplement these data with annual financial information from the Census of Governments, which reports local government debt, cash and securities, and tax revenue. We also collect county-level annual unemployment rate data from the Bureau of Labor Statistics.

C. Natural Disaster Data

To identify counties experiencing natural disasters, we use the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS reports the 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 span January 1960 through December 2018. Because we do not observe the exact disaster date, we assume that it occurred on the **last** day of the month.

We focus on meteorological events and aggregate reported damage to 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 a small amount of damage, we define “disasters” as county-month events associated with more than \$3 per-capita damage, which corresponds to 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, there are 25,455 county-months with disasters in 2005–2018.

Gallagher (2021) shows that SHELDUS underreports 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 experience a 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 reduces the possibility of control group contamination. Nonetheless, this concern motivates us to restrict our

sample of control counties to those that are at least 500 miles away from the disaster-affected county: Extreme weather is spatially correlated, and a larger buffer zone around disaster-affected counties therefore lowers the possibility of classifying a disaster-affected county as a control. Furthermore, because our preferred measure of “natural disaster” consists of slightly more than one-third of reported SHELATUS 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 damage.

We obtain data on federal disaster aid to households and local governments from the Federal Emergency Management Agency (FEMA). In the US, governors of disaster-affected states can request a federal emergency or major disaster declaration. To be eligible for federal disaster aid, a state must demonstrate that the event is so severe that state and local resources are insufficient to respond to it effectively. Although there are some objective metrics FEMA uses to assess eligibility—such as per-capita damage—there is no explicit formula, and the ultimate decision of 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 all but certain ex-ante. 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 localized, however, may not be eligible for federal disaster aid if the aggregate damage is relatively low.¹⁰ Conditional on a federal disaster declaration being granted, 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 the disaster location, declaration date, and amount of approved disaster aid. Data on the individual assistance program are at the zip code level, which we then convert to county-level. If a zip code falls into multiple counties, we assign it to the county with the largest

¹⁰Cases where a governor petitions for a federal disaster declaration but is denied are rare, likely because governors can first communicate with FEMA officials to assess the likelihood of the request being granted before applying.

population. Data on the public assistance and hazard mitigation assistance programs are at the project-level and report the county, declaration date, total project cost, and the federal contribution to the 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 variation in county-level federal disaster aid. First, the extreme event may not have affected a sufficient portion of the state 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 eligible for all three. 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 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 be better in disseminating information about aid eligibility and helping their residents apply. These sources of aid heterogeneity are not observable to us, however, and we discuss what they might mean for interpretation when we present our disaster aid analysis. We also discuss the implications of not observing damage perfectly.

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 return series at the county level. 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 of 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 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 is based on the following conceptual 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 interests) 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 idiosyncratic return component and is specific to each bond i . Using clean prices is advantageous to extract bond returns free from the price changes caused by accrued interests. In this sense, this model is equivalent to a market model expressed in log returns. By 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 weekly county-level returns R_t^c for $t = \{b + 1, \dots, s\}$. Weekly returns R_t^c are estimated as coefficients on weekly indicator variables in panel regressions. The indicator variables are equal to one for all weeks 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 squared root of bond issue amounts divided by the squared root of the time length between $b + 1$ and s . Thus, larger issues and more recent trades will receive larger weights, similar to 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.¹¹ In addition to aggregate bond return

¹¹In theory, using future returns could contaminate our pre-disaster estimates with post-disaster price changes. In

series, we also apply the repeat sales methodology to GO and REV bonds separately and construct county-level returns for each bond type.

Using the repeat-sales method, we obtain weekly county-level bond returns for 920 counties, which is a huge improvement over the conventional method, which requires trade data for consecutive weeks for the same bond. Panel A in Figure 1 shows that repeat-sales estimation generates return series for more than 30% of counties that have outstanding municipal bonds in the US. By contrast, the 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 the coverage implies that it is practically difficult to study the effect of natural disasters using the conventional method of bond return construction. Panel B in Figure 1 further shows that only 2.9% of the bonds are weekly traded and 0.88% of the bonds are traded daily. Even at monthly frequency, there are only 8.1% of bonds 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 1 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 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. 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 $\tau \in [-15, 20]$:

$$WCAR_{t,c,\tau} = \sum_{s=-15}^{\tau} (R_{t+s}^c - R_{t+s}^b).$$

The variable R_{t+s}^c is the weekly return for county c in week $t + s$ (i.e., s weeks after the disaster), estimated using the repeat sales approach. R_{t+s}^b is the weekly benchmark return, equal to the

practice, this does not appear to be a concern, as our pre-disaster coefficient estimates are always close to zero and statistically insignificant.

average return of the benchmark counties in week $t + s$.

Our main regression model uses the following specification to isolate the effect of a natural disaster that affects county c 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 equal to one when $t' = \tau$ and equal to zero otherwise. The coefficient, $\beta(t')$, thus captures the effect 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 be $t' = -2$. $D_{c,t,\tau}(p)$ is an indicator variable equal to one if county c experiences another natural disaster p weeks before $t + \tau$ and equal to zero otherwise. Similarly, $E_{c,t,\tau}(q)$ is an indicator variable equal to one if county c is within 200 miles of one or more other counties experiencing another natural disaster q weeks before $t + \tau$ (regardless of whether those other counties have bonds in our estimation sample). These two sets of variables help us separate the effect of natural disasters from the effects of other disasters hitting the same county or nearby counties. We set $P = 50$ and $Q = 40$.¹² Values of $P \in [20, 65]$ and $Q \in [5, 65]$ yield similar results. Because returns 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 effects, α_c . Only observations falling within the time window of interest, $\tau \in [-15, 20]$, are included in the estimation.

One challenge of implementing the repeat sales approach at weekly frequency is that the week indicator variables are subject to the collinearity problem if there are no bond trades in a given county for consecutive weeks. To address this, we drop extreme weather events that have more than 10% of collinearity in repeat sales estimation within the time window.¹³ Standard errors are three-way clustered by week-year t , the number of weeks since the disaster τ , and county c .

To attribute the post-disaster coefficients $\beta(t')$ for $t' \geq 0$ to the causal effect of the disaster on municipal bond prices, it must be the case that, absent the disaster, municipal bond prices in

¹²This choice is based on a trade-off between smaller bias and power. Using larger P and Q controls for more possible spillover effects but decreases degrees of freedom.

¹³See Section II.A for more details about collinearity in repeat sales estimation. Removing this filter doesn't change the results, but it creates additional noise.

disaster-affected counties would have evolved similarly to those in benchmark counties. While this 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 further allows us to assess whether disaster-affected counties exhibit any differential trends relative to benchmark counties. Finding that $\beta(t') = 0$ for $t' \leq 0$ would provide strong evidence for the identification assumption in our context.

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

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

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 equals zero otherwise. The coefficient $\beta(t')$ thus captures the effect of the disaster on cumulative returns over this time period, relative to $t' = -2$. All other variables are as in Equation (1), but defined at the monthly level.¹⁴

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:

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

This specification is advantageous to reduce potential noise in prices and therefore achieves better statistical power. Because clustering by the number of months from the disaster would leave us with only two clusters on this dimension, standard errors in Equations (2) and (3) are clustered by county and by year-month.¹⁵

¹⁴ P equals 12 and Q equals 10 in this monthly-level regression.

¹⁵ Additionally, clustering by number of months from the disaster does not meaningfully alter our results.

C. Summary Statistics

Table I presents summary statistics for key variables. Panel A shows that the average county-level weekly return is -0.001% with a standard deviation of 1.54%. REV bonds 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.

[Insert Table I here]

Panel B of Table I shows summary statistics for county-months with natural disasters, using our preferred damage per capita cutoff of 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 of property damage with a standard deviation of \$1226 million. Both aggregate and per-capita damage have a long right tail: 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 are insured, respectively. The average maturity of GO bonds is 6.85 years while that of REV bonds is 0.98 years longer. REV bonds tend to have 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 Results

Although natural disasters can create short-term negative shocks to local economies by destroying production capital and damaging infrastructure, it is ex-ante unclear how municipal bond prices will respond to disasters, for four reasons. First, it is ultimately revenues of local governments for GO bonds and project revenues for REV bonds that should matter for municipal bond cash flows. The extent to which natural disasters negatively affect revenues of municipal bond issuers is not a settled empirical question. Second, it is also not clear how natural disasters affect local economies in the long run. The pricing of municipal bonds is forward-looking, and thus price responses should reflect both the short- and long-run effects of natural disasters. In theory, disasters can even lead to higher economic growth, which is also known as the “build back better” hypothesis (Hsiang and Jina, 2014).¹⁶ 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. Finally, bond insurance may make the financial condition of the local government irrelevant for bond returns, at least for existing bonds. These considerations also 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 2 shows estimates of Equation (1), using estimated coefficients $\beta(t')$ to plot cumulative abnormal returns of uninsured municipal bonds around the event window (15 weeks before and 20 weeks after natural disasters). Panel A shows that, compared to benchmark counties, county-level bonds experience significant price declines after disasters, averaging approximately 0.25% in fifteen weeks. The price declines are persistent, lasting over 20 weeks, which indicates elevated risk for municipal bonds in disaster-affected areas. Note also that bond prices respond almost immediately, highlighting the effectiveness of our repeat-sales approach in discern the price impact of natural disasters. Reassuringly, the pre-disaster coefficients are very small and statistically insignificant, supporting the plausibility of the parallel trends assumption necessary to attribute the post-disaster

¹⁶Deryugina et al. (2018) and Groen, Kutzbach, and Polivka (2020) find that Hurricane Katrina victims’ income increased in the longer run; Lackner (2018) shows that wealthy countries experience long-run expansion after earthquakes. Roth Tran and Wilson (2020) also find positive long-run effect of disasters. Botzen, Deschenes, and Sanders (2019) conclude their paper by stating that “more research is needed on long-term impacts (e.g., beyond 5 years) of natural disasters.”

coefficients to the effect of the disaster itself.

[Insert Figure 2 here]

Panel B in Figure 2 show that the price impact is substantially larger for REV bonds, suggesting that it depends on the repayment source. Specifically, the cumulative abnormal return of REV bonds fifteen weeks after a disaster is -0.42% and the price impact appears to be non-reverting for at least 20 weeks following the disaster (Panel B). We also find that post-disaster cumulative returns tend to be flat, suggesting that bond investors are neither too pessimistic (price over-reaction) nor optimistic (price under-reaction) about natural disasters.

By contrast, Panel C shows that natural disasters have little effect on GO bonds. 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 natural disasters are not expected to impair broad economic conditions of municipalities and point to cash flow source diversification as an important determinant of municipal bond returns in the aftermath of natural disasters. Carroll (2009) documents that a greater degree of revenue diversification reduces revenue volatility. Our results complement these findings insofar as municipal debt backed by diversified cash flow sources—general tax revenues—exhibits greater resilience to natural disasters than municipal debt backed by single projects or assets.

To alleviate potential high-frequency noise in weekly returns, we repeat our analysis using monthly returns (Table II). In Panel A, we use one post-disaster indicator to estimate the average price impact in the post-disaster period. The results echo those in Figure 2, showing a price drop of approximately 0.31% after a disaster. As before, the price effect is concentrated in REV bonds (coefficient estimate of -0.51% with a t -statistic of -2.56). On the contrary, we find small (-0.13%) and statistically insignificant price effects for GO bonds.

[Insert Table II here]

In Panel B of Table II, we present monthly coefficients on cumulative abnormal returns following natural disasters. Consistent with the results depicted in Figure 2, we find that bond prices negatively react to natural disasters gradually over four-months. The peak of the impact appears to be 3 months after disasters, measuring 25 basis points for all bonds and 54 basis points for

REV bonds. Overall, we confirm that the price impacts of natural disasters on REV bonds are substantial and persist for weeks.

B. Insured Municipal Bonds

Municipal bonds are often guaranteed by insurance that covers coupon and principal payment against default. This credit enhancement scheme allows insured bonds to inherit bond insurers' credit rating. 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 sample, 56% of the bonds are insured overall, but only 19% of them are insured in 2009 or later.

Comparing price responses of insured and uninsured bonds helps achieve two goals. First, finding price impacts mainly in uninsured bonds would strengthen the evidence that bond prices fall because natural disasters jeopardize municipal issuers' repayment capability, not because of other behavioral reasons unrelated to physical disaster damage. Second, it is not clear ex-ante if bond insurance provides an effective guarantee against disaster risk, and a comparison of insured and uninsured bonds is thus informative about the market's perception of bond insurance effectiveness. Table III replicates the analysis in Table II using insured bonds only. The results imply that bond insurance eliminates the price effect of natural disasters, suggesting that market participants believe that bond insurance mitigates the disaster risk faced by municipal bonds. The contrast between insured and uninsured bond returns helps 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 its financial implications.

[Insert Table III here]

C. The Role of Disaster Severity and Federal Disaster Aid

We next examine how the price impacts of natural disasters vary with damage severity and the amount of federal disaster aid received by the affected county, focusing on uninsured bonds. Beyond measuring heterogeneity in the price response along these important dimensions, these estimates

also shed light on the extent to which investors’ rational assessment of damage matters for bond price responses and on the extent to which financial transfers lower the cash flow risk of municipal bonds in disaster-affected areas.

We first split our sample based on whether the estimated per-capita damage is above or below the median. In the above-median damage sample, the average per-capita damage is \$269 with the median of \$11.0. On the other hand, the below-median damage sample represents \$5.89 for the average per-capita damage, with the median of \$5.31. Comparatively, price declines are substantially larger for uninsured bonds of counties hit by above-median damages (Figure 3, Panel A) and are driven almost entirely by REV bonds (Panel B). Weekly abnormal cumulative returns of uninsured REV bonds in counties with above-median damage drop by almost 0.70% within fifteen weeks following a disaster. By contrast, we find essentially no price impacts for GO bonds even for disasters with above-median severity (Panel C), suggesting that cash flow source diversification makes bond prices resilient to both larger and smaller natural disasters. In neither sample, we find no evidence of differential trends prior to events.

[Insert Figure 3 here]

Before presenting concise difference-in-difference estimates of heterogeneity by disaster severity, we examine weekly price dynamics with respect to federal disaster aid. Graphs A1, B1, and C1 in Figure 4) show what happens to uninsured bond returns of counties that receive no federal disaster aid. As before, GO bonds are unaffected (Graph 1 in Panel C), and thus the overall decline observed in Panel A1 is driven entirely by REV bonds (Graph 1 in Panel B). Although damage in these counties is substantially lower than among counties that receive at least some aid (average per-capita damage of \$54 versus \$336), the price decline is very similar to that of counties experiencing above-median damage, suggesting that federal disaster aid plays an important role in post-disaster price dynamics.

[Insert Figure 4 here]

To examine the role of federal disaster aid further, we split the sample into counties that received above- or below-median federal disaster aid, as measured by aid per dollar of damage. Counties that receive no aid comprise about 60% of the below-median aid sample. The aggregate price response

among below-median-aid counties (Graph 2 in Panel A) is more muted than that of no-aid counties, although the average damage is substantially higher in the former group (\$522 per capita damage). This pattern is consistent with the value of aid being very high; alternatively, aid receipt could act as a signal of resilience to investors. Bonds of counties with above-median disaster aid exhibit no decline in returns, suggesting that the amount of aid received relative to damage also matters to investors. Where we do detect a significant decline in prices, it materializes quickly (within five weeks), suggesting the decline is driven by the disaster aid process itself rather than any rebuilding, which typically takes much longer.

The damage reported by SHELDDUS is likely to be a noisy measure of true damage. The measurement error, however, should bias us toward finding no heterogeneity by federal disaster aid per dollar of damage. This is because areas with more severe damage should, on average, receive more disaster aid. Because greater damage almost certainly causes larger price decreases, all else equal, unobserved damage would counteract any positive effects of federal disaster aid, driving the estimated price effect toward zero. Thus, the true heterogeneity in price responses by federal disaster aid could be even larger than what we estimate.

Table IV uses a difference-in-difference specification to concisely summarize the results of Figures 3 and 4 (Panels A and B, respectively). Post-disaster prices of uninsured REV bonds in counties experiencing above-median disaster severity are 0.61% lower (t -statistic of -1.83). By contrast, the price response of REV bonds to below-median disaster severity is more than three times smaller and statistically insignificant. Estimates for GO bonds are always small and statistically insignificant.

[Insert Table IV 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). The economic magnitude of these estimates is substantially larger than the average price decline reported in Table II. By contrast, uninsured REV bonds issued by counties with above-median disaster aid experience (statistically insignificant) price declines of only 0.30%. Consistent with the previous results for GO bonds, we do not find significant bond price changes for any level of disaster aid.

These estimates imply that federal disaster aid is very important for alleviating disaster risk to

municipal bonds backed by undiversified revenue sources. Because the final amount of federal disaster aid for any given disaster may not be known for some time following the event, our estimates are likely driven by ex-ante investor expectations. These expectations in turn could 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.

D. Financial Leverage of Local Governments

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. We hypothesize that the difference is due to the cash flow sources of GO bonds—overall municipal revenue—being more diversified than those of REV bonds, which are typically backed by a single project. The diversification hypothesis implies that GO bonds issued by municipalities that have less maneuvering room—for example, those with high leverage—can be negatively affected by natural disasters if natural disasters undermine municipalities’ creditworthiness.

To examine whether GO bonds experience significant price declines when the financial conditions of their issuers are poor, we first use data from the Census of Governments to calculate the debt-to-tax-revenue ratio for each county in the year prior to the natural disaster. Based on this ratio, we define a binary variable, $Levered_c$, equal to one if county c is in 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. Because the impact of local financial conditions likely depends 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 very low disaster (per-capita damage in the bottom tercile).

Table V shows that severe disasters have negative price effects on GO bonds of counties with high financial leverage (Column 2). The estimated coefficient on the interaction term between the high leverage and post-disaster indicators is -0.55% with a t-statistic of -2.33 , indicating that GO bonds of issuers in poor financial conditions experience substantial price declines after severe natural disasters. This finding is consistent with our hypothesis insofar as the diversification benefit

of tax revenues is low when counties are in poor financial standing. Financial leverage does not seem to matter for returns of GO bonds issued by counties affected by less severe disasters, however (Column 1).

[Insert Table V here]

Table V also shows that local financial conditions are not relevant for 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.

E. Government Revenue at Risk

Bonds issued by whose revenue is more exposed to natural disaster shocks should experience greater price declines. A simple measure of such exposure is the share of government revenue coming from local sources (as opposed to transfers from state and federal governments). We consider revenue to be concentrated on 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.

The results, reported in Table VI, show that the resilience of GO bonds to natural disasters disappears in counties with a high revenue concentration when they experience the most severe natural disasters (Column 2). When disaster severity is in the top tercile, the returns of GO bonds fall by 0.55% more 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. By contrast, although GO 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).

[Insert Table VI here]

IV. Discussion and Conclusion

Although extreme weather events are by definition infrequent, they regularly cause great damage to areas around the world. Climate change is increasing the frequency and intensity of such events, but we have yet to fully understand their implication for investors and local financing. We estimate the extent to which natural disasters—extreme weather events that result in 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 920 counties in the US, providing the first evidence on the risk of natural disasters to municipal bond investors.

We document that natural disasters have immediate negative impacts on municipal bond prices for counties that are hit by natural disasters. Compared to similar counties without disasters,

We find evidence that federal disaster aid alleviates the negative price impacts substantially. Financial conditions of municipalities also matter, as the price of general obligation (GO) bonds issued by counties with high financial leverage declines substantially following natural disasters. Geographical concentration in sources of revenue is also important: counties that rely heavily on their own tax revenues have more negative returns on their GO bonds when hit by natural disasters.

While approximately 42% of municipal bonds are owned directly by households who may be more 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. Our results indicate a form of slow-moving capital, by which the price declines do not materialize immediately after the disaster. Nevertheless, the patterns of heterogeneity and the relative stability of the price declines in the post-disaster period are all 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 the natural disaster, the patterns of results combined with the fact that many investors are households residing in or near the affected area imply that our findings may at least be partly due to increased risk aversion.

It is also possible ex-ante that *salience* plays a key role in how municipal bond investors react to natural disasters. Ex-post, however, the results are inconsistent with a simple salience story. 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 so. Likewise, the financial conditions of one's local government are not salient characteristics.

How much natural disaster risk will raise future municipal bond yields depends on the extent to which municipalities mitigate this risk by shifting to GO bonds or bonds that are insured. If climate change causes natural disasters to be more 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. Regardless, 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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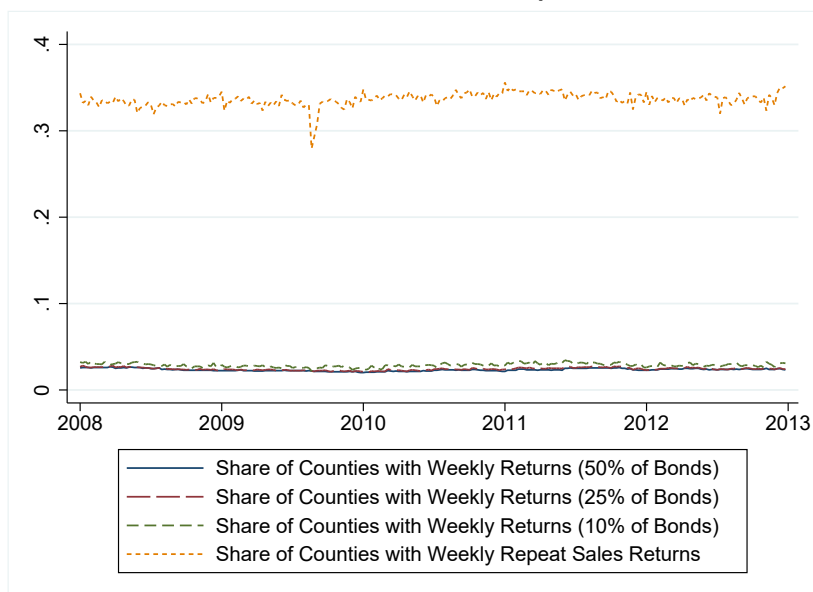
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Figure 1. The Frequency of Municipal Bond Transactions and Returns

The figure illustrates return data availability and municipal bond transaction frequency. Panel A plots the fraction of counties with weekly bond returns. A county has a weekly return at week t if a given percentage (50%, 25%, 10%) of outstanding bonds issued by the county have returns at t . The denominator is the number of counties with outstanding municipal bonds at t . Panel A also shows the share of counties with weekly repeat sales returns, 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

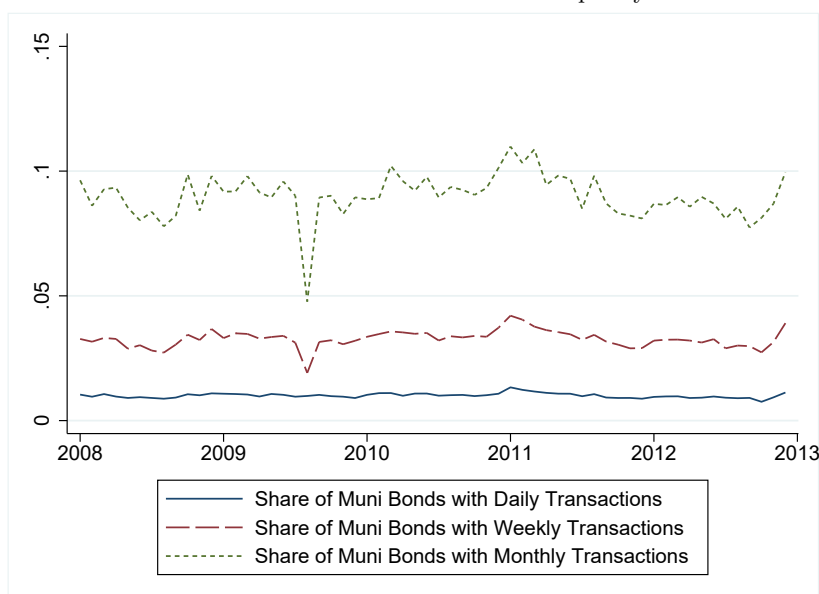


Figure 2. Cumulative Abnormal Returns Around Natural Disasters: GO vs. REV Bonds

The figure plots weekly county-level cumulative abnormal returns, in percent, of uninsured municipal bonds estimated using Eq. (1). Returns 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 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.

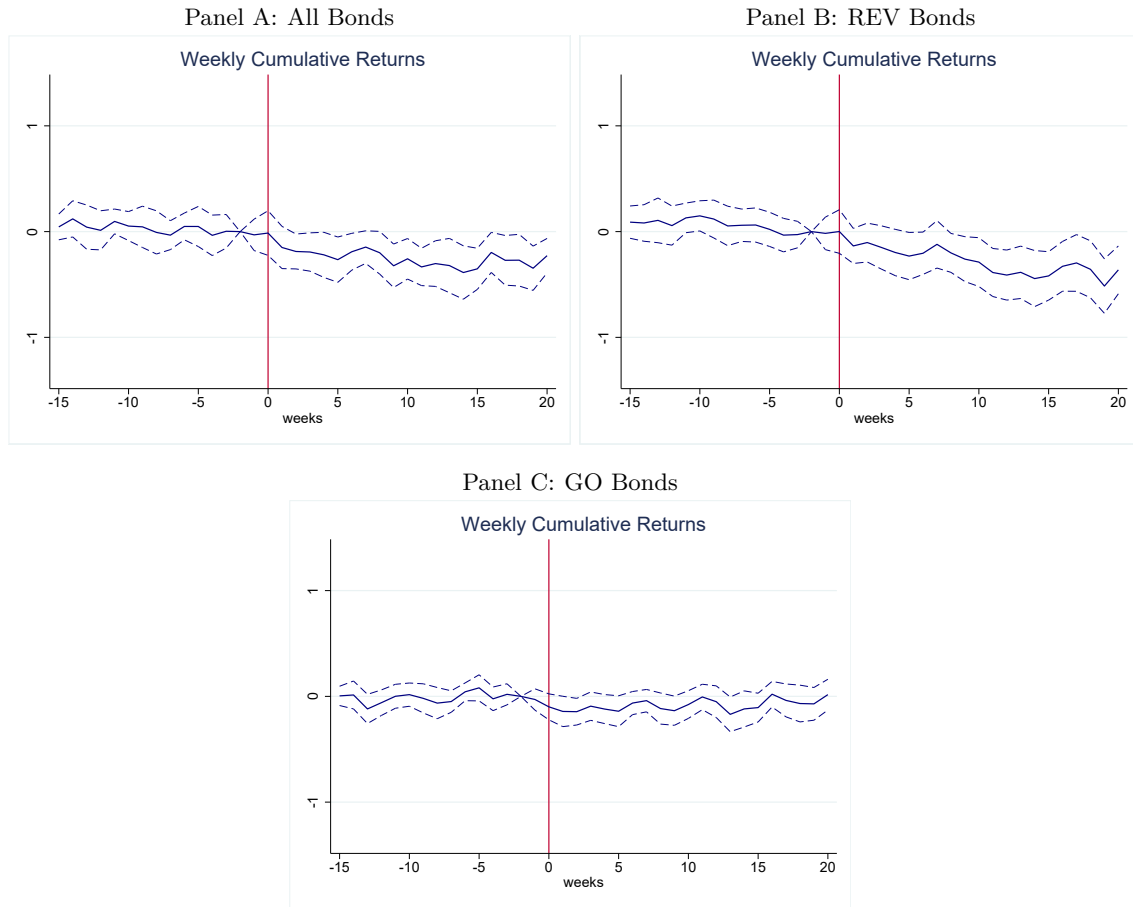
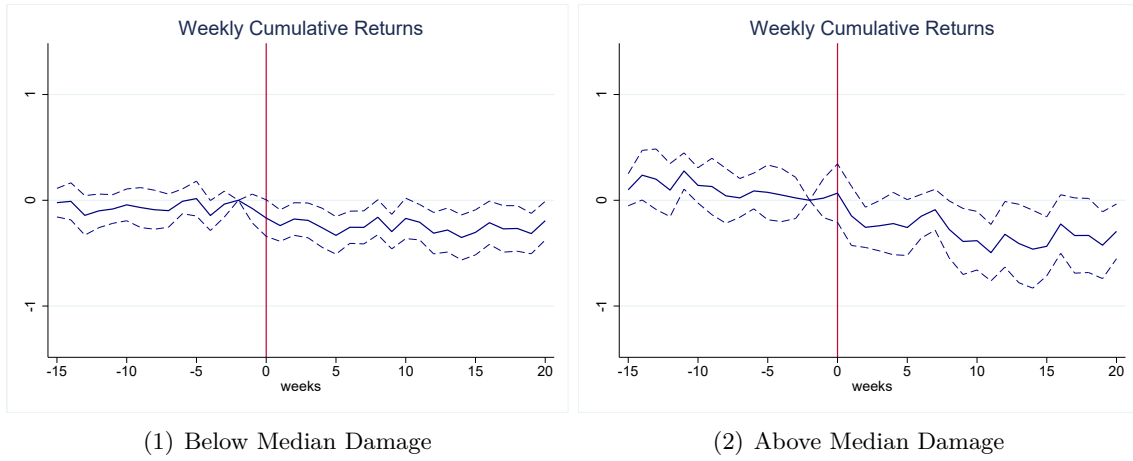


Figure 3. Cumulative Abnormal Returns Around Natural Disasters: Disaster Severity

The figure plots weekly county-level cumulative abnormal returns, in percent, of uninsured municipal bonds estimated using Eq. (1) separately for counties experiencing above- and below-median damage per capita. Returns 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 subsample 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 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: All Bonds



Panel B: REV Bonds



Figure 3 (Cont.). Cumulative Abnormal Returns Around Natural Disasters: Disaster Severity

Panel C: GO Bonds

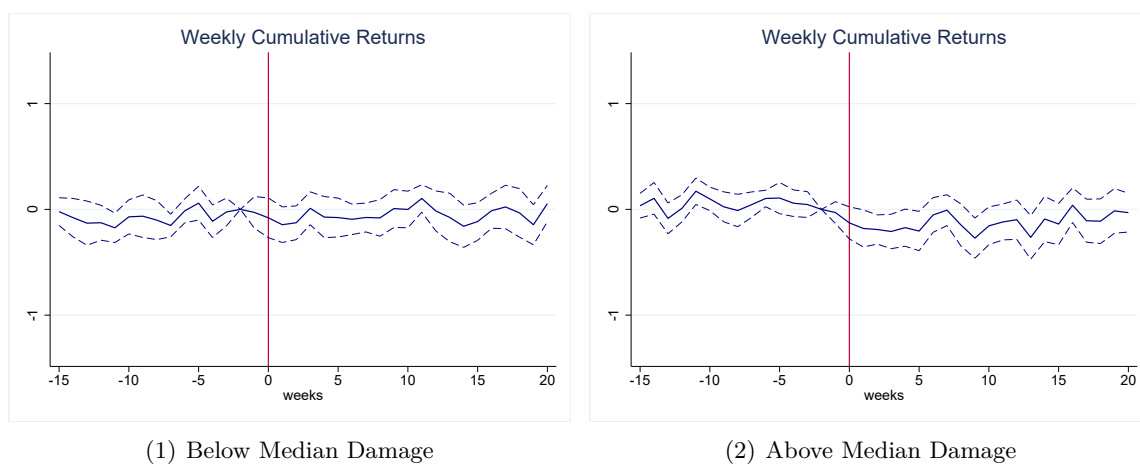
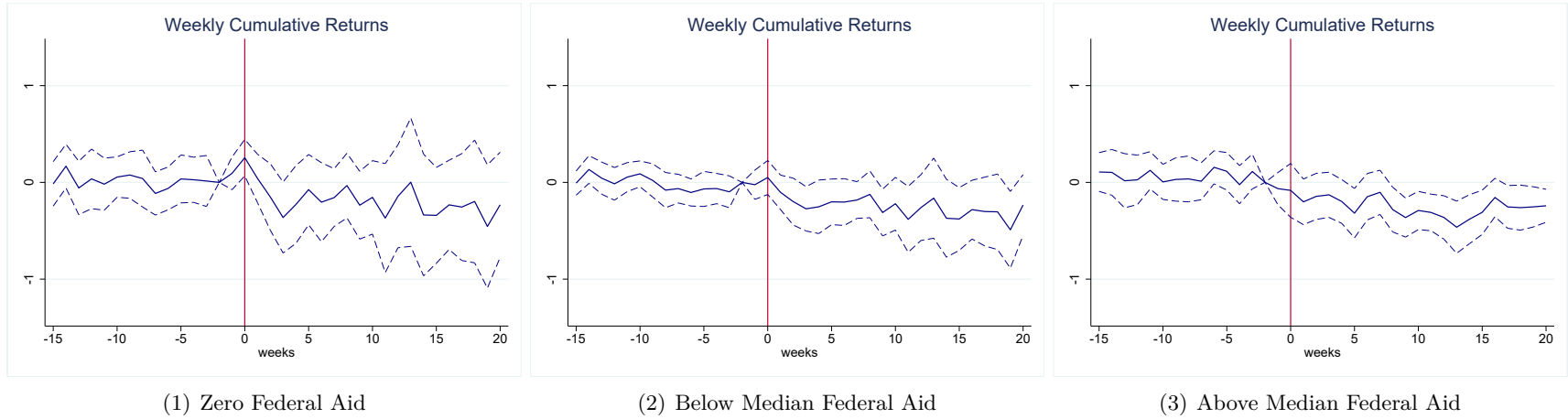


Figure 4. Cumulative Abnormal Returns Around Natural Disasters: Federal Disaster Aid

The figure plots weekly county-level cumulative abnormal returns of uninsured municipal bonds estimated using Eq. (1) separately for counties receiving zero, above-median, and below-median federal disaster aid per dollar of damage. Returns 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 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: All Bonds



Panel B: REV Bonds

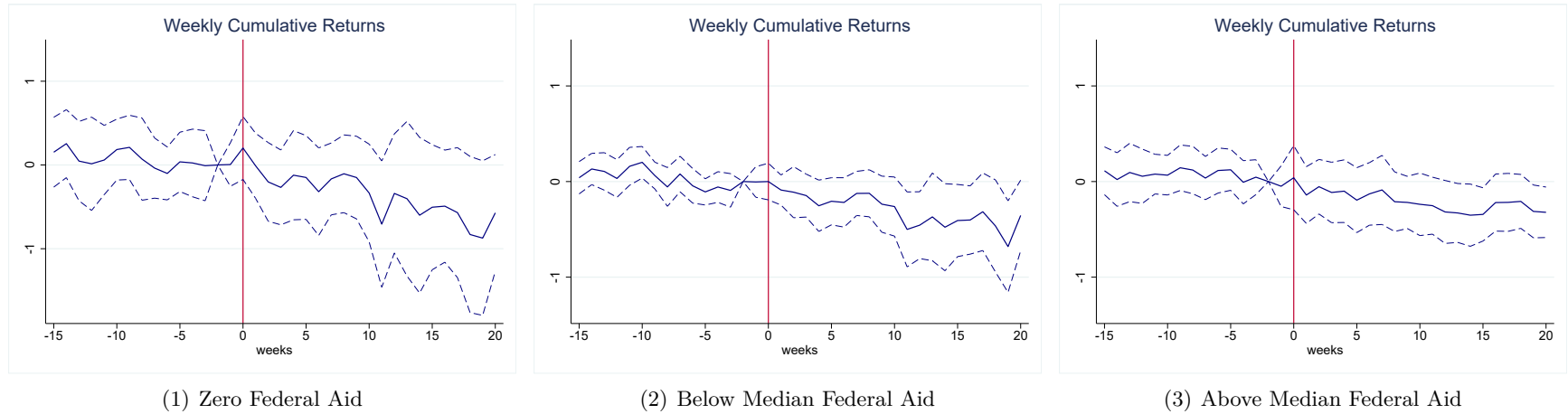
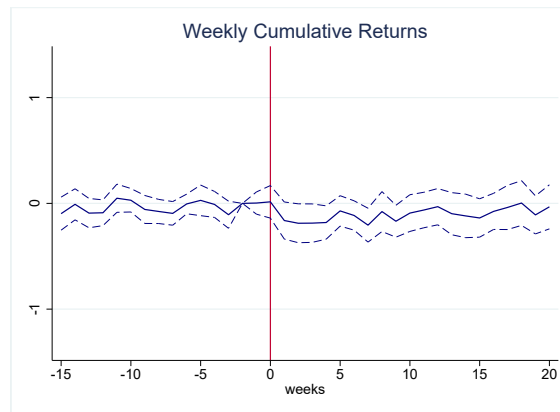


Figure 4 (Cont.). Cumulative Abnormal Returns Around Natural Disasters: Federal Disaster Aid

Panel C: GO Bonds



(1) Zero Federal Aid



(2) Below Median Federal Aid



(3) Above Median Federal Aid

Table I Summary Statistics

This table reports summary statistics for weekly county-level bond returns, natural disasters, and various county characteristics from 2005 to 2018. Panel A reports 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 (%)*) only uses REV (GO) bonds for the estimation. Panel B reports the summary statistics for natural disasters that have estimated returns from repeat sales using all bonds and county characteristics. Natural disasters are defined as the event that has normalized damage greater than equal to 1. Per-capita damage is defined as the sum of property damage and crop damage divided by the population. Injuries (Fatalities) is the number of people in a county who had injuries (fatalities) from a disaster. Panel C reports the summary statistics of characteristics of counties that have repeat sales returns and experienced natural disasters. Average county-level municipal bond characteristics are using par-value of each bond at issuance as a weight. *Avg Insured GO* and *Avg Insured REV* are average proportion of outstanding insured bonds of each type. *# of Bonds Outstanding* is the number of outstanding municipal bonds issued by a county. Maturity is 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 of 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: GO vs. REV Bonds

This table reports estimates using Eq. (3) (Panel A) and Eq. (2) (Panel B). The dependent variable is monthly cumulative abnormal returns, in percent. 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** (-2.3279)	-0.5089** (-2.5602)	-0.1277 (-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 (-0.5141)	-0.13 (-1.0794)	0.0748 (1.1645)
M(0)	-0.0397 (-0.4465)	-0.1666 (-1.5147)	-0.0414 (-0.4966)
M(1)	-0.0997 (-0.9475)	-0.3318** (-2.4351)	-0.0391 (-0.4536)
M(2)	-0.2031* (-1.7785)	-0.3817** (-2.3219)	-0.1196 (-1.1282)
M(3)	-0.2470** (-2.2873)	-0.5423*** (-3.0557)	-0.1055 (-0.9218)
M(4)	-0.2235* (-1.8391)	-0.4717*** (-2.6482)	-0.0251 (-0.2220)
County FE	YES	YES	YES
No. of Obs.	6990	4150	4606
Adj. R-Squared	0.4	0.39	0.35

Table III Natural Disasters and Insured Municipal Bonds

This table reports estimates using Eq. (3) for the sample of insured municipal bonds. The dependent variable is monthly cumulative abnormal returns, in percent. 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 (-1.2862)	-0.1419 (-1.5319)	-0.06 (-0.5195)
County FE	YES	YES	YES
No. of Obs.	3191	2052	1987
Adj. R-Squared	0.25	0.2	0.3

Table IV Disaster Severity and Federal Disaster Aid

This table reports estimates of Eq. (3) by disaster severity (Panel A) and by federal disaster aid amounts (Panel B). 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						
Dep Var: CR	Below Med REV Bonds	Above Med REV Bonds	Below Med GO Bonds	Above Med GO Bonds		
Post	-0.3502 (-1.5429)	-0.6132* (-1.8343)	-0.1243 (-0.7799)	-0.1986 (-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	Zero Aid REV Bonds	Below Med REV Bonds	Above Med REV Bonds	Zero Aid GO Bonds	Below Med GO Bonds	Above Med GO Bonds
Post	-1.1954* (-1.9769)	-0.7086** (-2.3249)	-0.2969 (-1.2096)	-0.0458 (-0.1882)	-0.2433 (-1.3574)	-0.1557 (-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 V Government Debt-to-Tax Ratios and Bond Returns Around Disasters

This table reports estimates of Eq. (3), split by disaster severity and augmented with an interaction term between the post-disaster indicator and an indicator for the county falling into the above 67th percentile of debt-to-tax-ratios. Low (high) severity indicates disasters in the bottom (top) tercile of severity. The dependent variable is monthly cumulative abnormal returns, in percent. 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	Low Severity	High Severity	Low Severity	High Severity
	GO Bonds	GO Bonds	REV Bonds	REV Bonds
Post $\times$ Levered	-0.0548 (-0.2199)	-0.5517** (-2.3262)	-0.0635 (-0.1459)	0.2924 (0.6155)
Post	-0.1518 (-0.9086)	-0.0142 (-0.0600)	-0.4773* (-1.7731)	-0.5838* (-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

Table VI Revenue-at-risk and Bond Returns Around Disasters

This table reports estimates of Eq. (3), split by disaster severity and augmented with an interaction term between the post-disaster indicator and an indicator for the county falling into the above 67th percentile 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 percent. 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 Q1-Q4	Severity Q5	Severity Q1-Q4	Severity Q5
	GO Bonds	GO Bonds	REV Bonds	REV Bonds
Post×Concentrated	0.2266 (0.7484)	-0.5454* (-1.9232)	0.2388 (0.3992)	-0.01 (-0.0176)
Post	-0.3643 (-1.3679)	-0.0652 (-0.2497)	-0.4649 (-0.8535)	-0.8143 (-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. Revenue Concentration Persistence

This figure plots the average local government revenue concentration for each of its lagged quintile from 2016 to 2018. The revenue concentration is a count-year level variable measured as Hirfindahl-Hirschman index (HHI) across three sources of general revenue of local governments: intergovernmental (IG) revenue from federal government, IG revenue from state government, and revenue of own sources.

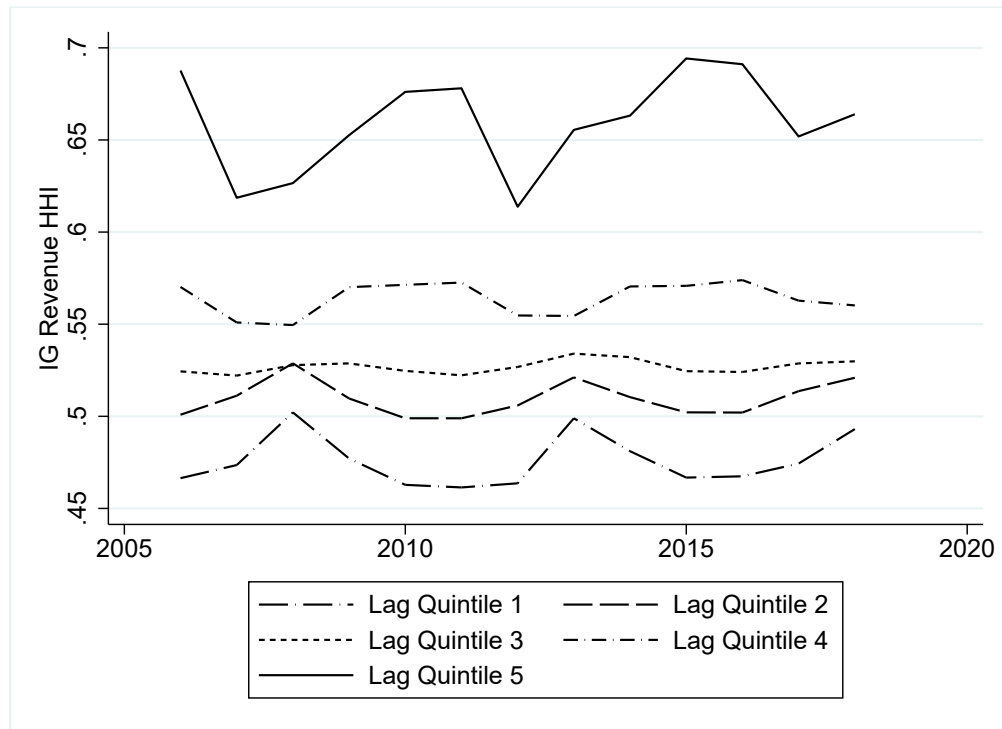


Figure A2. Geogrphaic Distribution of Uninsured GO and REV Bond across Counties with Disasters

This figure reports geographical distribution of counties with natural disasters that have issued GO bonds and REV bonds at least once during the sample period. Counties that are highlighted with blue have issued both GO bonds and REV bonds. Red (yellow) indicates counties that have only issued GO (REV) bonds.

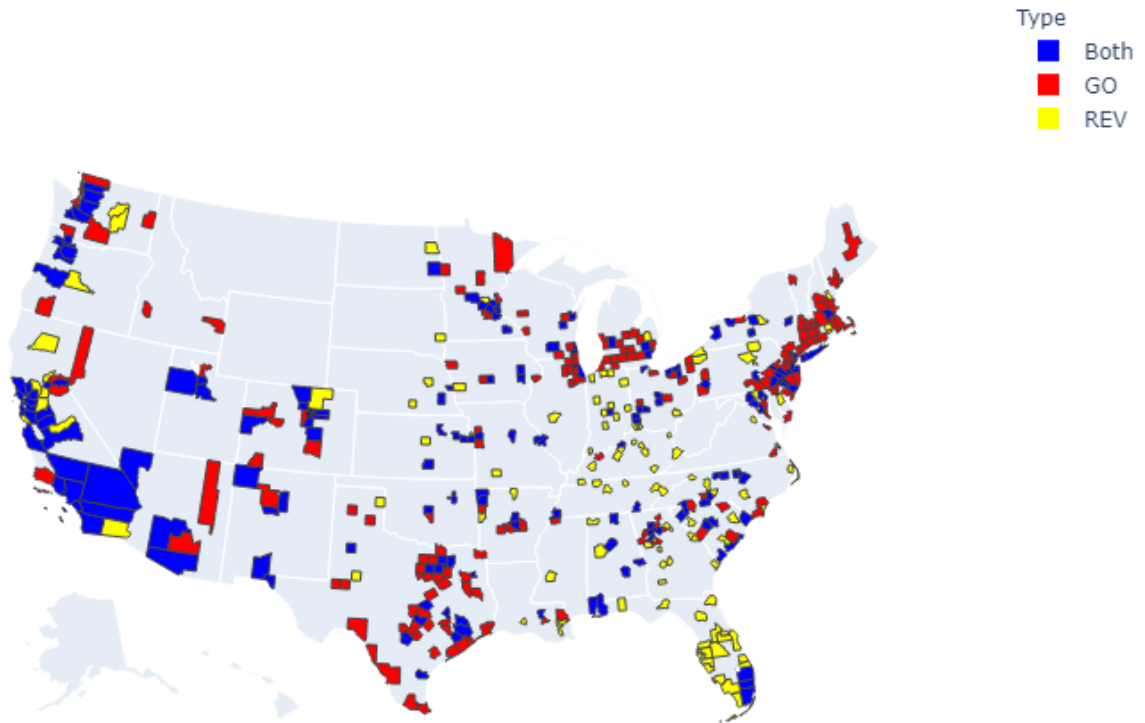


Table A1 Repeat Sales Estimation - All Bonds

This table reports summary statistics of the number of counties that repeat sales 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 presents the number of counties that have enough number of returns to implement repeat sales methodology for each year. Column 1 displays the number of counties that have returns estimated by repeat sales using all bonds - both GO and REV bonds. Column 2 and 3 report counties with repeat sales estimation using REV bonds and GO bonds, respectively. Panel B reports the summary statistics for weekly returns of municipal bonds, estimated using the repeat sales method.

Panel A: Number of Counties Estimated by Year

Year	# of Counties		
	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

This table reports estimates using Eq. (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 (-0.7621)	-0.0313 (-0.3498)	-0.0108 (-0.1825)
M(0)	-0.0804 (-1.3715)	-0.0429 (-0.4529)	-0.0414 (-0.7594)
M(1)	-0.0924 (-1.4865)	-0.0964 (-0.9728)	-0.0521 (-0.7258)
M(2)	-0.0627 (-0.9802)	-0.0208 (-0.2120)	-0.0679 (-0.8093)
M(3)	-0.1214** (-2.0565)	-0.1411 (-1.2651)	-0.1500** (-2.1514)
M(4)	-0.1255* (-1.7382)	-0.1314 (-1.0962)	-0.099 (-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 Transfer and Severity

This table reports estimates of Eq. (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 (-0.5822)	-0.1648 (-1.0885)	0.0106 (0.1441)	0.1472 (1.5930)	-0.1774 (-1.4175)	-0.0961 (-0.7713)	0.0677 (0.6861)	0.0644 (0.7720)
M(0)	-0.1849 (-1.5467)	-0.1281 (-0.7815)	0.002 (0.0256)	-0.0917 (-0.8250)	-0.1826 (-1.5576)	-0.1857 (-1.0565)	0.0678 (0.5537)	-0.1367 (-1.1678)
M(1)	-0.2932* (-1.9385)	-0.4468** (-2.0901)	0.0126 (0.1245)	-0.1236 (-0.9625)	-0.3836** (-2.1181)	-0.2431 (-1.5380)	-0.063 (-0.4679)	-0.0626 (-0.6799)
M(2)	-0.2983** (-2.0578)	-0.5227* (-1.8764)	-0.0787 (-0.5917)	-0.1806 (-1.3820)	-0.3140* (-1.6796)	-0.3820** (-2.2007)	-0.1068 (-0.7934)	-0.1867 (-1.5158)
M(3)	-0.3336** (-2.1227)	-0.7603*** (-2.6562)	0.0253 (0.1756)	-0.2605* (-1.7239)	-0.5842** (-2.2385)	-0.4535** (-2.2568)	-0.0636 (-0.4069)	-0.2081 (-1.5774)
M(4)	-0.3344* (-1.8815)	-0.5638* (-1.9467)	0.0264 (0.1885)	-0.0712 (-0.5023)	-0.6208** (-2.5635)	-0.2884 (-1.4383)	-0.0229 (-0.1559)	-0.1061 (-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

This table reports summary statistics of the share of each local government revenue source. First, in Panel A, we slice county-year level local government total revenue into three pieces: own sources, intergovernmental (IG) revenue from federal government, and IG revenue from state government. We then report fraction of each revenue source, denoted as *% Own Sources*, *% IG Revenue Federal* and *% IG Revenue State*, respectively. *Concentrated* is an indicator that equals 1 if a county is at the highest quintile of Hirfindahl-Hirschman index calculated using weights of these three revenue sources. In Panel B, we present summary statistics of the fraction of each local tax type. We redefine *Concentrated* as an indicator that equals 1 if a county is at the highest quintile of Hirfindahl-Hirschman index calculated using weights of individual tax types.

Panel A: Intergovernmental Revenue Sources Summary Statistics

Type	Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Concentrated=0	% Own Sources	62.9	10	28.4	56.8	64.2	70.3	99.2	1531
	% IG Revenue Federal	3.4	2.6	0	1.5	3	4.5	17.4	1531
	% IG Revenue State	33.7	9.8	0.8	26.4	32.5	39.6	67.8	1531
Concentrated=1	% Own Sources	80.5	6.7	20.2	77.6	81	83.4	94.9	368
	% IG Revenue Federal	2	1.6	0	0.7	1.6	2.7	8	368
	% IG Revenue State	17.6	7	3.1	14.2	17.5	20.5	79.3	368

Panel B: Tax Sources Summary Statistics

Type	Variable	Mean	Stdev	Min	p25	p50	p75	Max	Count
Tax Concentrated=0	Property Tax	57.572	39.372	0	0	72.587	89.885	100	979
	Total General Sales Taxes	10.819	19.027	0	0	0.887	16.546	100	979
	Alcoholic Beverage Sales Tax	0.449	6.382	0	0	0	0	100	979
	Amusement Tax	0.546	7.134	0	0	0	0	100	979
	Insurance Premium Tax	0.36	5.539	0	0	0	0	100	979
	Motor Fuels Sales Tax	0.036	0.252	0	0	0	0	3.627	979
	Parimutuels Tax	0.005	0.067	0	0	0	0	1.248	979
	Public Utilities Tax	4.419	17.938	0	0	0	2.266	100	979
	Tobacco Sales Tax	0.323	5.53	0	0	0	0	100	979
	Other Selective Sales Taxes	3.588	16.604	0	0	0.089	1.077	100	979
	Alcoholic Beverage License Tax	1.545	12.288	0	0	0	0.001	100	979
	Amusement License Tax	0.42	6.383	0	0	0	0	100	979
	Corporation License Tax	0	0.007	0	0	0	0	0.172	979
	Hunting & Fishing License	0	0	0	0	0	0	0	979
	Motor Vehicle License	1.814	12.671	0	0	0	0.094	100	979
	Motor Vehicle Operators Lic	0.102	3.196	0	0	0	0	100	979
	Public Utility License Tax	0.469	6.391	0	0	0	0	100	979
	Occup & Business License, NEC	4.569	19.743	0	0	0	0.565	100	979
	Other License Tax	6.255	22.907	0	0	0.305	1.161	100	979
	Indiv Income Tax	2.084	9.772	0	0	0	0	100	979
	Corporation Net Income Tax	0.033	0.344	0	0	0	0	7.07	979
	Death & Gift Tax	0.121	3.198	0	0	0	0	100	979
	Documentary & Stock Trans Tax	1.045	9.064	0	0	0	0	100	979
	Severance Tax	0.206	4.517	0	0	0	0	100	979
	Taxes, NEC	3.221	16.375	0	0	0	0.123	100	979
Tax Concentrated=1	Property Tax	77.364	39.801	0	87.845	97.967	99.225	100	241
	Total General Sales Taxes	1.556	9.312	0	0	0	0.402	100	241
	Alcoholic Beverage Sales Tax	0	0	0	0	0	0	0.007	241
	Amusement Tax	0	0.002	0	0	0	0	0.024	241
	Insurance Premium Tax	0	0	0	0	0	0	0	241
	Motor Fuels Sales Tax	0	0	0	0	0	0	0	241
	Parimutuels Tax	0	0	0	0	0	0	0	241
	Public Utilities Tax	1.78	12.794	0	0	0	0.078	100	241
	Tobacco Sales Tax	0	0	0	0	0	0	0	241
	Other Selective Sales Taxes	2.654	15.59	0	0	0	0.251	100	241
	Alcoholic Beverage License Tax	2.091	14.281	0	0	0	0.001	100	241
	Amusement License Tax	0.002	0.017	0	0	0	0	0.202	241
	Corporation License Tax	0	0	0	0	0	0	0	241
	Hunting & Fishing License	0	0	0	0	0	0	0	241
	Motor Vehicle License	0.074	0.439	0	0	0	0	5.488	241
	Motor Vehicle Operators Lic	0	0	0	0	0	0	0	241
	Public Utility License Tax	0.007	0.039	0	0	0	0	0.374	241
	Occup & Business License, NEC	2.165	14.272	0	0	0	0.082	100	241
	Other License Tax	9.755	28.673	0	0	0.657	1.355	100	241
	Indiv Income Tax	0.002	0.039	0	0	0	0	0.602	241
	Corporation Net Income Tax	0	0	0	0	0	0	0	241
	Death & Gift Tax	0	0	0	0	0	0	0	241
	Documentary & Stock Trans Tax	0.869	9.088	0	0	0	0	100	241
	Severance Tax	0.833	9.091	0	0	0	0	100	241
	Taxes, NEC	0.847	9.089	0	0	0	0	100	241