Uncharted Waters: Pollution and Municipal Finance

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Abstract

We show that pollution increases municipal bonds' offering yields and yield spreads, indicating increased risk. We establish this using a difference-in-differences design comparing the bonds from the U.S. counties revealed to contain per- and poly-fluoroalkyl substances (PFAS) in their drinking-water supplies with the bonds from neighboring, unpolluted, same-state counties. The increase was more for riskier bonds characterized by repayment obligation, *ex-ante* debt burden, credit rating, maturity, and bankruptcy access. The resulting pollution-related investment needs and a reduction in public employment and expenditure likely underlie the risk. An instrumental variable-like method utilizing airports as potential PFAS source reaffirms the causal interpretation.

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> *As the full scope and cost of the need for [PFAS] remediation is not yet known, the Massachusetts Municipal Association (MMA) remains deeply concerned over how municipalities could pay for what has already been and will continue to be exorbitant cleanup costs.*
>
> — Geoffrey C. Beckwith, CEO, MMA.

Municipalities play a crucial role in local economic development for it is them who plan, build, and maintain public infrastructure, and deliver public goods and services at the hyperlocal level. Over time their role is becoming even more important as the share of public services under their ambit is increasing (Baicker, Clemens, and Singhal, 2012), and their financial constraints have a strong bearing on local employment (Adelino, Cunha, and Ferreira, 2017; Dagostino, 2018), economic growth (D. Green and Loualiche, 2021), and the quality of public services (Yi, 2020).

The goal of this paper is to examine whether pollution affects the borrowing costs (bond yields) of the municipalities and thus adds to their financial constraints. We find that bond yields of local municipalities increased when it was exogenously revealed that their area was contaminated with previously un-monitored contaminants. Public employment and expenditure subsequently shrunk, adversely affecting the local economic risk and likely contributing to the increased yields.

While municipal borrowing has been shown to be affected by the factors such as green certification (Baker, Bergstresser, Serafeim, and Wurgler, 2018), climate change (Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2020; Painter, 2020), environmental regulations (Jha, Karolyi, and Muller, 2020), and hurricanes (Jerch, Kahn, and Lin, 2020), the consequences of local pollution remain sparsely studied. What makes this research challenging is the reverse causality issue between pollution and municipal financing. It could be that more pollution makes municipal borrowing expensive, or that expensive borrowing constrains investment in pollution-abatement technologies leading to more pollution (Agrawal and Kim, 2021).

This paper addresses the challenge using a close-to-exogenous event in a difference-in-differences (DID) design. In August 2016, an unexpected finding came out from the nationwide testing of the drinking water in the U.S. under the third Unregulated Contaminant Monitoring Rule (UCMR 3). The drinking water supplies of almost two hundred counties across 33 states were found to be contaminated with the potentially fatal per- and poly-fluoroalkyl substances (PFAS), a set of pollutants not regulated or monitored in drinking water and hitherto untested for. The contamination came as a shock, it received widespread publicity (The Harvard Gazette, Aug 9, 2016; Hu et al., 2016), and Google searches for the keyword "PFAS" surged massively, and therefore we utilize this event in the DID design. The treatment group consists of the municipal bonds from the polluted counties, the control, the bonds from the bordering uncontaminated counties within the same state, and the sample period spans 2015 to 2017.

A crucial element of the DID strategy is the exogeneity of the event, i.e. the unpredictability of the timing and/or location of the contamination *ex-ante*, which the institutional environment surrounding the PFAS does suggest. Neither bound by any regulatory oversight nor covered under the drinking water safety standards, the pollutants flew under the radar un-watched and un-monitored until then. In fact, the UCMR (3) was the first national scale testing program for these chemicals, and even the tests available then had limited detection sensitivity (EPA, Jan 2017).[1] Taken together, these circumstances make it unlikely that the contamination locations could have been predicted.[2] The event in effect caused a sudden increase in the *information* on contamination levels of the affected counties, but it did not change the actual pollution, which may have occurred years or decades ago.[3]

The empirical strategy is distinctly suited to study the effects of pollution on municipal finance. *First*, the contamination of drinking water, as opposed to air or natural water bodies, allows us to demarcate the affected areas and the municipalities therein, since drinking water provision usually falls within geographic boundaries, i.e. coun-

[1] Sampling and analysis of PFAS require special precautions to avoid cross-contamination, and the best practices for it came from the U.S. Navy in 2015, after UCMR (3) (Dorrance, Kellogg, and Love, 2017).

[2] One may wonder, why the contamination occurred in some areas but not in others? The answer lies in the historical usage of the PFAS and their properties. For over five decades, the chemicals have been used in a multitude of consumer and industrial applications, whereas it was only in early 2000's that their adverse effects on human health were discovered, and only recently it is discovered that they can seep into the environment, including ground and drinking water. Then they are incredibly resistant to environmental degradation and thus are also knows as the "The Forever Chemicals". So while it is not well understood when and how some areas get contaminated, it is unlikely that the underlying processes, which may span several decades, correlate with the financial characteristics of the municipalities.

[3] We use the terms contamination and pollution interchangeably.

ties. *Second*, as the control municipal bonds are from the bordering counties in the same state, they are subject to similar economic conditions, common state policies and public finance related regulations, and therefore serve as reasonable counterfactuals. *Finally*, the short sample period limits the effect of confounding factors and thus allows for precise estimation.

The null hypothesis underlying our empirical investigation is that pollution has no effect on municipal finance. The baseline estimates comparing offering yields on new bonds suggest that the issuers from the polluted counties suffered an average increase of 5–6 basis points (bps) vis-à-vis the issuers from the neighboring, same-state, unpolluted counties. These estimates are robust to the inclusion of highly granular municipality fixed effects, time-varying state fixed effects, and a host of controls for individual bond characteristics and for county-level economic conditions.

Since the general upkeep of an area, including pollution control and drinking water provision, is the responsibility of the general-purpose municipalities, but not of the special-purpose ones, such as school and special districts, the latter should remain relatively uninfluenced. Consistent with this intuition, the effect for the former is 8–9 bps, statistically significant, while for the latter is just 2–3 bps, statistically insignificant. Economically, a 9 bps increase in offering yields of general-purpose municipalities is roughly equivalent to 3.7 bps increase in property taxes or $265 million increase in interest expenses in present value terms.

Consistent with a falsification test of pollution, the special-purpose municipalities did not see an increase in borrowing costs because these are relatively un-linked to pollution as they are somewhat shielded from fluctuations in the local (county-level) economic conditions due to various state and federal policies. Thus the rest of analyses focus on the general-purpose municipalities only.[4]

To determine whether it is risk that pushes the offering yields higher, the next set of regressions evaluates how the offering yields changed in the sub-samples of bonds

[4] While school districts receive significant revenue from state and federal governments and are subject to strict legal and regulatory oversight, many special districts earn revenues through service charges (say, park usage fees), thus their link to the general economic growth is less tightly linked than the general-purpose municipalities.

classified according to five alternate risk measures. Specifically the sub-samples consist of (i) water-related revenue bonds, general obligation (GO) bonds, and other revenue bonds; (ii) bonds of long and short maturity; (iii) bonds of low and high credit risk municipalities; (iv) bonds from counties with *ex-ante* high and low debt burden; and (v) bonds from states that have Chapter 9 municipal bankruptcy code and those that do not (Gao, Lee, and Murphy, 2019). Within each of these classification schemes, the estimates consistently show that relative to the control group, the offering yields in the treated group increased more for the former sub-group than the latter.

Notably, within the first classification scheme, the increase was massive 29–48 bps for water-related revenue bonds, 8–9 bps for fiscally important GO bonds, and statistically non-significant for non-water revenue bonds. This suggests that the pollution affected not only the water-related municipalities through the increased needs of cleanup and pollution-abatement investment, but also the GO bonds, whose repayments highly depend on economic conditions of the local area.

To further reaffirm that the findings are causal, we use a strategy similar to an instrumental variable (IV) method. It is based on the idea that municipalities in the proximity of specific airports federally mandated to use PFAS are more likely to be contaminated than those near airports not mandated to use PFAS (Part 139 Certification of Airports, 2004). The exclusion restriction is that being close to the PFAS-using airports or the others does not differently affect the offering yields of municipal bonds. The analysis confirms that municipalities within 20 miles of the specific airports were more likely to have the drinking water contamination than those within 20 miles of the other airports, offering us a credible proxy for the contamination. Then, after the event, the offering yields of the former municipalities increased by 16–17 bps, statistically significant at the 1% level, whereas those of the latter increased by 8–10 bps, statistically significant at the 10% level. This differential increase in yields supports the causal conclusion that the revelation of pollution led to increase in offering yields of local municipalities.

A fundamental question then arises, which economic factors fueled the risk the municipalities face that led to the higher bond yields? One reason appears to be the changing expenditure pattern of the general-purpose municipalities. The expenditure in general category, education, and health *declined* in the polluted counties vis-à-vis the control, while expenditure on water infrastructure increased. Also, the public employment in the polluted counties dropped. Both these factors, which intricately affect local economic growth, likely contributed to the increased risk.

Even though yield spreads on already-issued bonds do not affect municipalities' borrowing costs, to understand investors' changing views on the risk of bonds issued by affected municipalities after the pollution was revealed, we examine the changes in the spreads. Consistent with the risk explanation, the spreads increased by 8–9 bps.

Overall, we show that pollution affects the municipal bond yields in a manner consistent with an increase in economic risk, and the economic forces likely underlying it are unfavorable deviations in local expenditure patterns and a drop in public employment. Thus local pollution can add to the financial constraints of municipalities.

This paper primarily contributes to the municipal finance literature. We establish a causal economic link between local pollution and municipal borrowing costs. In addition to those discussed earlier, the following factors have been shown to affect municipal bonds, listed in no particular order: opioid crisis (Cornaggia, Hund, Nguyen, and Ye, 2021; W. Li and Zhu, 2019), population aging (Butler and Yi, 2018), underwriter locations (Butler, 2008), dual municipal advisor and underwriter role (Garrett, 2021), corruption and political connection (Butler, Fauver, and Mortal, 2009), holding by mutual funds (Y. Li, O'Hara, and Zhou, 2020), reporting delay in bond transactions (Chalmers, Liu, and Wang, 2021), newspaper closures (Gao, Lee, and Murphy, 2020), and state's pension under-funding (Boyer, 2020; Novy-Marx and Rauh, 2012).

The current paper also adds to the water pollution literature, a new strand of the vast and mature literature on pollution. It has been shown that lead contamination of drinking water leads to declining consumer credit scores (Gorton and Pinkovskiy, 2021), increasing demand for visits to doctor's office (Danagoulian, Grossman, and Slusky, 2020), and depleting housing stock and rising public expenditure (Christensen, Keiser, and Lade, 2019), whereas ground water contamination results in depressed houses prices (Muehlenbachs, Spiller, and Timmins, 2015). We show that PFAS contamination of drinking water municipal made borrowing expensive and reduced local municipal expenditure and public employment.

1 Institutional Information

The PFAS

Per- and poly-fluoroalkyl substances (PFAS) are a family of thousands of synthetic chemicals, about 4,730 currently on record (OECD, 2018). Among them, the perfluorooctanesulfonic acid (PFOA) and perfluorooctanoic acid (PFOS) were invented the first, manufactured the longest, understood the best. A wide variety of consumer products and industrial processes historically made use of these chemicals, e.g. nonstick cookware, grease-resistant food packages, stain- and water-resistant clothes, shaving creams, and fire-fighting foams. Designated by the EPA as "Contaminants of Emerging Concern", PFOA and PFOS are highly toxic and extremely soluble in water and are being researched for developmental, reproductive, and systemic adverse health consequences (EPA, November 2017). They have already been linked to cancer, immunosuppression, endocrine disruptions, and cholesterol complications (Barry, Winquist, and Steenland, 2013; Grandjean et al., 2012; Sunderland et al., 2019; C8 Science Panel, n.d.). We briefly summarize in Figure (I) the key events related to the PFAS.[5]

The Event: Revelation of the PFAS

The PFAS were never monitored on a large scale in the drinking water supplies until the third Unregulated Contaminant Monitoring Rule (UCMR 3), under which the monitoring took place across the U.S. from January 2013 to December 2015 (Federal

[5] We do not attempt to describe the scientific advances on these chemicals and refer to Dorrance et al. (2017) for a brief non-technical discussion of PFAS manufacturing history, chemical properties and remediation challenges; to Johnson (2020) for a regulatory discussion; and to DeWitt et al. (2015) for a comprehensive technical discussion on its health effects.

Register, May 2, 2012, Exhibit 3: Timeline of UCMR Activities).[6] Relying on the data from the program, Hu et al. (2016) identified the PFAS contamination and made national headlines, such as in The Harvard Gazette (Aug 9, 2016), shown in Panel (A) of Figure (IV). The publication date of the report, August 9, 2016, serves as the event date in the DID design.

While it is not known when and how the drinking water supplies got contaminated, and while it must have occurred non-exogenously then, we argue that the *information flow* to the market about the contaminated locations is "close to exogenous". First, the Google searches for the keyword "PFAS" spiked massively on the event date resembling an information shock (Figure IV, Panel B), and relatively more searches came from the contaminated vis-à-vis non-contaminated states (Figure IV, Panel C).[7] Then, predicting the locations before the program was implausible as it would have needed a private monitoring at a national scale, a process that is uncertain, costly, and without incentives in the absence of enforceable safety standards.[8]

Consequences for the Municipalities

If the municipalities could recover the cleanup and remediation costs, or if these costs were trivial, yields on their bonds, whose repayments are tied to the local economic conditions, would not be affected. However, recovering the costs through legal means is uncertain, as the source of contamination itself is unclear. At the same time, the cleanup and treatment costs are significant, e.g., it cost $100 million investment and $3 million yearly maintenance to install a drinking water treatment equipment to remove

[6] UCMR requires EPA to monitor contaminants that do not have any set health-based standards but are known or anticipated to occur in public water systems (EPA, Jan 2017). Every five years, EPA prepares a list of candidate contaminants and monitors a maximum of 30 in *all* large water supply systems that serve more than 10,000 individuals and a *representative* sample of small systems.

[7] Google search interest index represents the degree of "search interest" for the keyword at any time relative to the highest point during the period of analysis over a given region (U.S. in the present case). In the time series, a value of 100 represents the peak popularity for the term. A value of 50 means that the term is half as popular. For the cross-sectional plot, first data spanning six-month intervals were obtained, then the mean was calculated within each interval for the two sets of states.

[8] It is costly as just the sample collection and testing cost under UCMR 3 the EPA about $87 million (U.S. Government Accountability Office, 2014). It is incentive-less as information on contamination location without any regulatory enforceable safety-standards are not actionable. The first non-enforceable guidelines, called life-time health advisory, were released on May 16, 2016 (EPA, 2016).

GenX, a PFAS, in Brunswick county, North Carolina (National Association of Counties, Apr 15, 2019). Then the contamination may also lead to lost opportunities, for example, the redevelopment plan of former Willow Grove military base and surrounding areas in Pennsylvania was stalled after the contamination was discovered (McDaniel, Nov 20, 2019).

The seriousness of the contamination is also reflected in the regulatory responses that followed. First, states made budgetary provisions for cleaning up the contamination and testing local population for adverse effects, and some considered upgrading infrastructure.[9] Second, local enforceable limits on PFAS were legislated.[10] More than 80 pieces of legislation were introduced in the 116$^{\text{th}}$ Congress (National Conference of State Legislatures, Jan 25, 2021), and a federal regulation concerning the PFAS in drinking water is being drafted (Federal Register, EPA, Mar 10, 2020).

2 Empirical Research Design

We employ a DID design based on the detection of PFAS in the drinking water under the UCMR 3 program: treatment group consists of the counties with positive detection, the control of the bordering counties that lie within the same state but did not have PFAS contamination, and August 9, 2016, serves as the event date. The sample consists of 123 treated counties and 210 control from across 30 states, shown on the map of the contiguous U.S. in Figure (II).[11] Specifically, all the local governments, municipalities,

[9] Pennsylvania set out $3.8 million in the state's budget to clean up Bucks and Montgomery counties (H.B. 1410, 2019; The Philadelphia Inquirer, Aug 23, 2019). Arizona's legislation cast aside funds from the state's general budget for contamination related expenses and free voluntary blood testing of residents (S.B. 1565, 2020). Alaska proposed legislation to provide for free the affected residents with safe drinking water and voluntary blood testing for up to three years, and to set stricter upper limits on the pollutants (S.B. 176, 2020). Then, New York Department of Health estimated that infrastructure upgrades worth $855 million and annual operating costs worth $40 million would be needed in the state of NY if a 10 parts per trillion (ppt) limit on PFAS is enforced (Toloken, Jan 09, 2019). New Hampshire postponed an enforceable limit on PFAS fearing prohibitive expenses of compliance (New Hampshire Department of Environmental Services, 2020; Ropeik, Jul 16, 2019)

[10] In contrast to the EPA's advisory of 70 ppt for PFOA and PFOS individually or combined, New Jersey set maximum contaminant levels (MCL) at 13 ppt for PFOS and PHNA (perfluorononanoic acid), and 14 ppt for PFOA (New Jersey Department of Environmental Protection, n.d.). Vermont's MCL is 20 ppt for PFOA, PFOS, PFNA, PFHxS (perfluorohexane sulfonic acid), and PFHpA (perfluoroheptanoic acid) in total (Vermont Department of Environmental Conservation, n.d.).

[11] The study reported contamination across 33 states, but our sample ends up three states short in the process of merging the contamination data with the municipal issuer and transaction data.

and other public issuers within the treated counties are considered treated.

We utilize the two-way fixed-effects (TWFE) estimator as specified below:

$$y_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \delta \text{ Controls}_{imcst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst} \tag{1}$$

where y_{imcst} is offering yield of municipal bond i issued by municipality m from county c of state s in year t. $Treatment_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data, and 0 otherwise. $Post_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 otherwise.

β_1, the coefficient of interest, captures the change in the dependent variable after the event in the treated counties relative to the control. All the regressions are estimated *with and without* co-variates, $Controls_{imcst}$. These vary across specifications and consist of a host of bond- and county-level economic variables.

α_{mcs} represents municipality fixed effects (the first FE in the TWFE). These account for any inherent time-invariable differences across municipalities. γ_{st} denotes "*State×Year*" fixed effects (the second FE in the TWFE). These flexibly account for any state-specific economic shocks or any policy changes, even if they arise in different years. Thus the inferences are robust to any state-level time-varying confounding factors, such as the political landscape, public borrowing policies, or economic fluctuations. Finally, to account for cross-sectional correlation, standard errors are clustered at the county level.

Is TWFE an appropriate estimator in the current DID design?

A key issue with TWFE estimator is that in *staggered* DID designs, it may aggregate individual treatment effects by assigning "negative weights" to them (Borusyak, Jaravel, and Spiess, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020). Since the estimator measures variance-weighted average of the treatment effects, the negative weights occur in staggered designs when the treatment effects are heterogeneous across time and/or the treated units (Goodman-Bacon, 2021). Since the current paper does not use a staggered DID design, but a *single-treatment* design, the issue of heterogeneous treatment effects across time does not arise. The second issue of treatment effects being heterogeneous across treated units remains a noteworthy limitation.

Time-varying co-variates also potentially introduce bias in the estimator (Goodman-Bacon, 2021), but the conclusions of this paper are robust to this issue, as all the estimates are qualitatively and quantitatively similar either *with or without* the co-variates. Finally, the estimator also requires random assignment of the treatment, which seems to hold as the timing and circumstances of the PFAS discovery appear unrelated to the municipalities' choice, as discussed earlier.

In the end, the key assumption the TWFE relies on is parallel-trends: the treated counties would have seen similar trends in local municipal bond yields relative to the control counties in the absence of the treatment. Though it is unverifiable, Figure (III) plots the trends of mean and median offering yields against year-month for the two groups before and after the event. Both Panel (A) and Panel (B) of the figure suggest that yields seem to be parallel before the event. The slight increase in mean/median offering yields for the treated group after the event represents the treatment effect.[12]

3 Data and Summary Statistics

We use three key pieces of data in this paper: PFAS contamination data from UCMR (3) program; municipal bond issuance and trade data from Thomson Reuters Eikon and Municipal Securities Rulemaking Board (MSRB), respectively; and local government expenditure data from the Annual Survey/Census of State and Local Government Finances, compiled by Pierson, Hand, and Thompson (2015) and public employment data from Annual Survey of Public Employment & Payroll (ASPEP). Furthermore, the data from Federal Aviation Administration (FAA) on airport certification and locations are used in the instrumental variable-like method, and data from Bureau of Economic

[12] The difference in the yields after the event may appear negligible in the plot as expected, since the change in offering yields are an order of magnitude smaller than the raw offering yields. Also, these plots do not control for crucial differences across municipalities, states, and bond's rating, maturity etc., and thus the plots may mask the true treatment effect, for which regressions provide robust estimates.

Analysis (BEA) are used to capture local economic conditions. The steps to process and link these data are provided in Data Appendix (Appendix A).

The municipal issuance data contain a host of new issue-related information such as yield, coupon, amount etc., and the trade data specify information such as trading yield and amount of transaction. The key variable of interest is riskiness of municipal bonds. For new bonds, riskiness is reflected in the *offering yield* (yield to maturity at issuance), whereas for the already-issued bonds, in yield spreads.[13]

Panel (A) of Table (I) shows key statistics on the contamination level for each of the six PFAS monitored under UCMR (3). Column (1) shows the number of counties in which a given contaminant was detected; Column (2), the fraction of counties affected by a given contaminant; Columns (3–6), the concentration statistics; and the last Column, the minimum reporting level (MRL, the lowest detectable concentration under the testing technology "Method 537"). For example, out of the 123 counties that had PFAS contamination, 84 (68.3%) had PFOA, with a mean detection level of 54.88 ng/L and a maximum of 349 ng/L, almost five times the EPA's lifetime health advisory.[14]

Panel (B) of Table (I) summarizes the municipal bonds and county's economic conditions. A typical newly issued municipal bond has offering yield (yield to maturity at issuance) of 2.16%, coupon of 3.5%, maturity of 9.5 years, and S&P rating between BBB and BBB- (we assigned the value 21 to AAA rating, 2 to D, and 1 to unrated bonds). Treated bonds are slightly smaller ($3.87 million vs 4.61), but are alike in coupon, offering yields, and credit rating. In terms of secondary market trading, the treated bonds have slightly higher yield spreads than the control, and they trade less (7.1 times per month vis-à-vis 7.7). With respect to economic conditions, treated counties have similar growth rates of gross domestic product (GDP) and income per capita to control but higher property taxes and intergovernmental revenues.

[13] We measure yield spreads at monthly interval. To calculate it, we first find yield spread of each transaction as its trading yield minus maturity-matched treasury yield (with linear interpolation to the nearest month), and then average the yield spreads over the month, weighted by respective transaction amounts. Owing to a lack of liquidity, a bond is excluded from spread calculation in a year if it traded less than 5 times in that year. Also, trades occurring within the last 12 months of maturity are excluded, as yields in these periods are noisy (Goldsmith-Pinkham et al., 2020; R. C. Green, Hollifield, and Schürhoff, 2007).

[14] Although PFAS was detected in 201 unique counties, our sample consists of 123 counties that satisfy the requirements of the empirical design, see Appendix (A) for details.

4 Results

4.1 Baseline Results: Pollution and Offering Yields

The empirical analysis begins with evaluating how the offering yields changed after the event. Specifically, we use the following regression:

$$\begin{aligned} \text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst} \end{aligned} \tag{2}$$

where *Off. Yld.* is offering yield of bond i (at cusip level) issued by municipality m from county c of state s in year t. β_1 is the coefficient of interest *Bond Controls*$_{imcst}$ are: bond size (in millions), coupon rate, S&P credit rating, tenure (in months), inverse tenure, and indicators for whether the bond is tax exempt and insured. *County Controls*$_{cst}$ include rates of growth of county GDP and income per capita, and property taxes and intergovernmental revenues (in millions). α_{mcs} is municipality fixed effects and γ_{st} is "*State*$\times$*Year*" fixed effects.

Table (II) shows the results of the above regression. The estimates of β_1 in Columns (1) and (2) suggest that a new bond issued by a municipality in a polluted county experienced a 5–6 bps increase in offering yields relative to a municipality from a neighboring uncontaminated county after the revelation of the contamination. Notably, with municipality fixed effects included, the interpretation is that bonds of the same municipality suffered increase in offering yields after the event.

Since it is the general-purpose municipalities who depend the most on local economic conditions, as opposed to the special-purpose municipalities who enjoy significant federal and state support, the impact on the former should be larger.[15] Estimating separately the effect on the two reveals that while the former faced 8–9 bps increase (Columns 3 and 4), the latter saw no measurable effect (Columns 5 and 6). A 9 bps increase in the offering yields, from the no-covariate specification (Column 3), is our

[15] *General-purpose* municipalities include county/parish (11), city/town/village (12), and local authority (16), whereas *special-purpose* include college or university (13), district/board of education (14), and direct issuer (21). The numbers in parentheses refer to the *issuer type code* in the SDC database.

preferred estimate of the effect of PFAS pollution on general-purpose municipalities' bonds. In the remaining analysis, we thus focus only on these municipalities.

Is a 9 bps increase in the offering yield economically large? This represents a 4.3% increase over the average yields the affected general-purpose municipalities paid in 2016 (before the event). In terms of present value, they would end up paying $265 million more in interests.[16] If financed solely through property taxes, they would need to raise property taxes by 3.7 bps to keep the revenue at the same level ($27 million interest payment as a fraction of $71 billion property taxes in 2017). From the perspective of the relative strength of the effect, in Figure (V) we compare the effect of pollution with that of other well-known factors. From the figure, pollution appears to be economically at least as crucial for municipal finance as these other previously studied factors.

In summary, the rise in offering yields of the affected municipalities and a higher jump for those with tighter economic links with the polluted areas support the conclusion that their borrowings were deemed riskier after the pollution was revealed.

4.2 Effect Heterogeneity by Risk Characteristics

To corroborate if the underlying reason for the increase in yields was driven by risk, we examine next whether the yields change in sync with various proxies of municipal risk.

I. Water revenue bonds vs general obligation bonds

Depending on the cash flows that back their repayments, municipal bonds are of two broad types. General obligation (GO) bonds, which account for a bulk of public borrowing, are backed by the taxing power of the municipalities while revenue bonds are backed by expected revenue streams of the projects underlying specific bond issues. The offering yields of GO bonds thus reflect overall creditworthiness of the issuer and are linked to the economic prospects of the locality, whereas those of revenue bonds reflect the riskiness of only the project revenue streams, not the general local economy.

[16] These municipalities from the polluted counties borrowed $30 billion in bonds with average maturity of 119 months in 2017. 9 bps, or $27 million in annual interest payments, capitalized over the average maturity using the treasury rates for 1, 2, 5, 7 and 10 year in 2017 amount to about $265 million.

Thus the effect of drinking water pollution on offering yields should be the strongest for the revenue bonds linked to water provision, moderate for the GO bonds owing to their links with the economic growth, and the least for the other revenue bonds unrelated to water provision.

To test the above prediction, we estimate Equation (2) separately for the three types, and present the result in Table (III). The offering yields increased for the affected municipalities vis-à-vis the control by 29–48 bps for revenue bonds related to water provision (Columns 1 and 2) and by 8–10 bps for GO bonds (Columns 3 and 4), but those did not increase for revenue bonds unrelated to water provision (Columns 5 and 6).

The findings confirm the prediction and also suggest that pollution affects local economy not just through the directly linked (water) municipalities, but through all the economically dependent municipalities, including the GO borrowers.

II. Long vs short maturity bonds

Longer maturity bonds are riskier than the ones with shorter maturity, thus given that pollution makes municipal borrowing riskier, the increase in offering yields should be larger for the former. Since maturity was controlled for in all baseline regressions, the estimates reflected the effect averaged across maturity. We now examine the effect of pollution separately for long (>15 years) and short maturity bonds ($\leq$ 15 years) using Equation (2) and present the result in Table (IV). Consistent with the risk explanation, longer maturity bonds experienced larger increase (13 bps, Columns 1 and 2) than those with shorter maturity (8 bps, Columns 3 and 4).

III. Ex-ante high versus low debt-burden counties

Municipalities from the counties that have *ex-ante* higher debt burden have higher repayment risk than those from low debt-burden counties. Thus given that pollution makes municipal borrowing riskier, the increase in offering yields should be larger for the former. We use the ratio of county-aggregated debt of all the sub-state municipalities ("county, municipal, and township governments") to their aggregated revenue as a measure of county debt burden. A county is then assigned to the low-debt burden group if its debt burden in the pre-event year (2015) was less than the cross-sectional mean across all counties, and to high-debt burden otherwise. We examine the effect of pollution separately for the two groups using Equation (2) and present the result in Table (V). Consistent with the risk explanation, relative to the control, the treated municipalities in *ex-ante* high debt burden counties experienced larger increase (10 bps, Column 2) than the low group (7 bps, Column 4).

IV. Low vs high credit-risk municipalities

Credit risk of a municipality is a prime determinant of its offering yields. Higher the credit risk, stronger would be the effect of pollution on offering yields. Since municipalities often issue a mix of unrated and rated bonds, and since even the bonds in the same issue often have different credit ratings, assessing credit risk of municipalities by just using bond ratings may misrepresent the risk. Moreover, unlike the corporation ratings, the municipalities ratings update irregularly and may not capture a change in risk occurring within a short time horizon. We thus devise an intuitive and fast-updating proxy for credit risk that can be applied to any municipality, even the ones who issue unrated bonds. It is the ratio of unrated bond issuance amount to total issuance amount by a municipality in a year, and larger this value, higher is the credit risk. Using this proxy, a municipality is of high risk if in the pre-event year 2015, its ratio is less than the cross-sectional average calculated separately for the treated and control municipalities, and of low risk otherwise.

We estimate the effect separately for the two groups using Equation (2) and present the results in Table (VI). Columns (1) and (2) suggest that the *ex-ante* high credit-risk municipalities experienced an increase of 11–20 bps relative to the control municipalities of similar risk, whereas Columns (3) and (4) suggest that those with *ex-ante* low credit risk experienced an increase of just 2–5 bps relative to the municipalities of similar risk. The finding is consistent with the risk explanation.

V. Municipalities with vs without access to Chapter 9 bankruptcy

Municipalities in the states that allow (Chapter 9) municipal bankruptcy are riskier than those from the states that prohibit such access (Gao et al., 2019). Thus given that pollution makes municipal borrowing riskier, the increase in offering yields should be larger for the former. We examine the effect of pollution separately for these two set of municipalities using Equation (2) and present the result in Table (VII). Consistent with the risk explanation, with respect to the control, the treated municipalities in the Chapter 9 states experienced larger increase (11 bps, Columns 1 and 2) than the treated municipalities in the non-Chapter 9 states (7–9 bps, Columns 3 and 4).

To summarize, the differential increase in yields along each of the five measures that capture a different dimension of risk suggests that pollution affects the pricing of municipal bonds through the risk channel.

4.3 Effect on municipal expenditure and public employment

Keeping the increase in municipal bond yields in mind, the question arises, what underlying economic forces may have altered the municipal risk? To uncover this, we examine municipal expenditure and public employment using the same DID strategy.

Following the similar economic logic as before, the effect on expenditure should be stronger for the general-purpose municipalities as opposed to the special-purpose municipalities (school and special districts). We thus compare municipal expenditure in the polluted counties with surrounding unpolluted counties separately for these two group of municipalities.[17] The regression equation is as follows:

$$\text{Expenditure}_{mcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \beta_2 \text{ Revenue}_{mcst} + \alpha_{mcs} + \gamma_t + \varepsilon_{mcst} \quad (3)$$

where m refers to a municipality from county c in state s, and α_{mcs} and γ_t are municipality and year fixed effects, respectively. $Post_t$ takes the value of 1 for $t > 2016$ and 0 otherwise. Since expenditures are a function of revenues, the regressions control for it. Following Cornaggia et al. (2021), expenditures and revenues are standardized as log dollar amount *per capita* for the general-purpose municipalities and as log dollar

[17] In the government finance data, municipal (2) and township (3) governments constitute the general-purpose municipalities, and special district (4) and school district governments (5), the special-purpose, where the numbers in parentheses indicate the *government type codes*.

amount for the special-purpose, to which the concept of serviceable population, and hence per capita measure, does not apply. Finally, standard errors are clustered at the municipality level.

For brevity, we show the key coefficients collected from the individual regressions in Panel (A) of Table (VIII). The "DID" coefficients in Column (1) suggest that polluted counties experienced a significant decline in direct general expenditure, and expenditure on education and health, while a significant increase in expenditure on water utilities (these expenditures are defined in Table A.1). Thus expenditure on water utilities appears to have increased at the expense of other crucial categories including health. Given that expenditure loss is an important indicator of fiscal distress, the findings suggest that pollution adds to the adverse economic effects through municipal distress.

In contrast, the coefficients in the Column (4) suggest that the expenditure by special-purpose municipalities increased in many categories in the polluted counties vis-à-vis the control, and so did their long-term debt. In summary, even though both these types of municipalities faced similar economic environment, the type affected by the pollution decreased the expenditures while the type unaffected increased.

To examine pollution effect on the public sector employment, we use the following regression:

$$\begin{aligned} \text{Public Employment}_{cst} = \; & \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \text{ County Controls}_{cst} \\ & + \alpha_{cs} + \gamma_{st} + \varepsilon_{cst} \end{aligned} \tag{4}$$

where c refers to county, s to state, and t to year; and standard errors are clustered by county. The results of the regression are shown in Panel (B) of Table (VIII). The dependent variable in Columns (1) and (2) is one plus natural log of public employment, and the coefficients suggest that the employment in the polluted counties decreased by about 26–33% with respect to the unpolluted counties. The dependent variable in Columns (3) and (4) is the share of public employment in total employment, and this also dropped by about 2 percentage points. In effect, these estimates are not only highly statistically significant, but also economically huge given that public sector is often one of the largest employers.

4.4 An Instrumental Variable-like Approach

The DID analysis so far strongly suggests that the yields increased after the pollution was revealed, however it is based on monitoring of large drinking water supplies (serving >10,000 population) and a *representative* sample of small supplies, but not all. UCMR (3) did not monitor most small public water systems, nor the private wells, thereby omitting the water supplies of about one-third of the U.S. population (Hu et al., 2016). We thus turn to an empirical strategy inspired by the instrumental variable method that not only generalizes the findings to beyond the areas that were monitored, but also reaffirms the causal interpretation.

Depending on the operational scale, airports in the U.S. are assigned an Aircraft Rescue and Fire Fighting (ARFF) index ranging from A to E, and all but index A airports are *mandated* to use in firefighting the Aqueous Film-forming Foams (AFFF), which primarily consists of PFAS (Part 139 Certification of Airports, 2004).[18] Further, for operational readiness purposes, the FAA requires the airports to test the firefighting equipment every 9 to 24 months (Federal Aviation Administration, 29 Oct 2019, 2020). Thus we classify those indexed B–E as *polluting* and those indexed A as *non-polluting* airports, as the former discharge PFAS into the ground regularly and have high potential to contaminate the nearby areas. Figure (VI) shows the locations of 420 certified airports in 2016, of which 217 are polluting and 203 non-polluting.[19]

We use the location of the two types of airports as a proxy for PFAS contamination and examine how the offering yields of the municipalities within 20 miles of the two types of airports changed after the event. The exclusion restriction is that the location of the two different types of airports affects the yields of bonds of nearby municipalities only through the differences in their potential to contaminate surrounding areas,

[18] Owing to their excellent petroleum-based fire suppression properties, AFFF are exceptionally suited for usage at airports, and that is probably why despite the adverse health effects, FAA mandated airports to use these in the past. FAA has now initiated some steps to minimize the AFFF usage at airports (Federal Aviation Administration, 29 Oct 2019).

[19] Even though the ARFF index of airports may change, such changes are rare and few. For example, in the 2020 FAA certification, the change from B to A occurred only for 1 out of 521 (0.2%) certified airports.

not through other mechanisms. The restriction seems plausible since we restrict our focus only to the areas surrounding airports, with some surrounding polluting airports, while other, non-polluting.

We begin by estimating the following spatial autoregressive model using a generalized spatial two-stage least squares estimator to validate the proxy (Anselin, 2013).[20]

$$\text{PFAS Contamination}_z = \beta_0 + \beta_1 \text{ Polluting Airport}_{z \leq 20} + \lambda\ \mathbb{W} \times \text{PFAS Contamination}_z + \varepsilon_z \tag{5}$$

where the dependent variable is a zip code-level contamination measure, and the sample includes all zip codes within 20 miles of the certified airport. *Polluting Airport*$_{z\leq 20}$ is a dummy variable equal to 1 if the airport within 20 miles of a zip code z is polluting one and 0 if non-polluting. $\mathbb{W}$ is a queen contiguity-based spatial weighting matrix (taking the value of 1 for bordering zip codes and 0 for others), and "$\mathbb{W}\times$ *PFAS Contamination*$_z$" denotes the spatially lagged dependent variable, inclusion of which accounts for the spatial diffusion of pollution. The direct effect of a polluting airport on nearby contamination is captured by β_1, the coefficient of interest.

Panel (A) of Table (IX) shows the results of the above regression for three dependent variables measuring contamination: whether a zip code z had a PFAS contamination (a dummy variable), the maximum detected PFAS concentration (among the six PFAS tested), and the PFOA concentration. The coefficients suggest that as opposed to a non-polluting airport, the presence of a polluting airports within 20 miles is associated with a 1.3% probability of PFAS contamination (Column 1), a 11.86 parts per trillion (ppt) PFAS contamination (Column 2), and 1.1 ppt PFOA contamination (Column 3). In effect, the specific airports indeed predict the contamination, validating the first stage of the IV.[21]

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[20] This model is needed to account for the spatially correlated nature of a contamination process. Waters of spatially closer areas are likely to get contaminated together, and the contamination could reach from polluting airports (direct effect) and from neighboring areas which first for contaminated from the airport (indirect effect).

[21] Similarly, Ahrens, Norström, Viktor, Cousins, and Josefsson (2015) link the PFAS contamination around the Arlanda airport of Sweden to the airport's chemical usage, Høisæter, Pfaff, and Breedveld (2019) document ground water contamination with PFOS due to AFFF usage at Norwegian firefighting training facility, and Adamson et al. (2020) link AFFF usage to PFAS around U.S. military installation.

Since the polluting airports predict PFAS contamination, we no longer need to restrict the focus to only the municipalities from the contaminated counties and surrounding uncontaminated counties. We thus now use the following regression to examine the offering yields for all the general-purpose municipalities located within 20 miles of a U.S. airport.

$$\begin{aligned}\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}.\end{aligned} \tag{6}$$

Panel (B) of Table (IX) shows the regressions results. We see that the municipalities near polluting airports witnessed a 16–17 bps increase in offering yields (Columns 1 and 2), whereas those close to non-polluting airports experienced far smaller increase of 8–10 bps (Columns 3 and 4).

All in all, this IV-like method reaffirms and generalizes the conclusion from the DID analysis that the revelation of pollution led to higher offering bond yields of the general-purpose municipalities.

5 Supplementary Discussion

This section describes additional findings that aid in interpreting previous conclusions and help in ruling out some alternative explanations.

I. Ameliorating effect of tax privileges

Given that bank-qualified bonds offer special tax privileges for the banks (Cornaggia et al., 2021) and that these bonds tend to be held largely by banks (Dagostino, 2018), the effect of pollution on these bonds would be smaller than not bank-qualified bonds. We thus examine the effect of pollution separately for the two groups using Equation (2) and present the result in Table (X). Consistent with the ameliorating effect of tax-privileges, not-bank-qualified bonds of affected municipalities saw a large 10 bps increase (Columns 1 and 2) relative to the bonds of the same type of the unaffected municipalities, whereas bank-qualified bonds saw a much smaller 4–6 bps increase, which is statistically not significant (Columns 3 and 4).

II. Effect on yield spreads of already-issued bonds

It's the offering yields on new bonds that affect the municipalities borrowing cost, not the yield spreads on already-issued bonds. Yet the yield spreads reflect investors' views on the risk of the municipalities, thus they should also rise if the pollution resulted in increased risk to municipalities. Another advantage of yield spreads analysis is that it allows to observe the changes in investors' views about the same bond over time. We use the following regression equation:

$$\begin{aligned}\text{Yield Spread}_{imcst} = \beta_0 + \beta_1\ \text{Treatment}_{cs} \times \text{Post}_t + \delta_1\ \text{Bond Control}_{imcst} \\ + \delta_2\ \text{County Controls}_{cst} + \alpha_{imcs} + \gamma_{st} + \varepsilon_{imcst}.\end{aligned} \tag{7}$$

The regression includes bond (cusip) fixed effects α_{imcs} and "*State*×*Year*" fixed effects γ_{st}. While *County Controls*$_{cst}$ are the same as in Equation (2), *Bond Control*$_{ijcst}$ include bond's remaining maturity at the time of transaction (in months) and its inverse, the number of trades in each month, and monthly standard deviation of its dollar price.

Table (XI) reports the results. The sample in Column (1) included all bonds, and the associated coefficient suggest that the yield spreads of the affected municipalities increased by 10 bps relative to the unaffected issuers. Similarly, the coefficients in Column (2) through (4) suggest that the differential increase in spreads was 14 bps for water-related revenue bonds, 9 bps for GO, and 12 for non-water related bonds. Then, Column (5) and (6) suggest that the spreads increased by 13 bps for municipalities from counties with *ex-ante* high debt burden, and by 10 bps for those from *ex-ante* low debt burden. In broad terms, the increased yields spreads too point to an increase in risk of the general-purpose municipalities from the polluted counties as perceived by investors, and the sub-sample patterns match with that observed for the offering yields.

III. Investors' preference for pollution-free investment

A capital-supply explanation could be that investors have preference for investing in pollution-free areas, in which case the revelation of the contamination may cause the yields to rise not because of increased municipal risk, but because of reduced supply of capital from such investors. Recall that longer-maturity bonds of the same municipalities experienced larger increase than their shorted-term bonds. Had the increase been driven by investor preference, all bonds of affected municipalities would experience increase. Similarly, special-purpose districts from the same polluted counties did not suffer any meaningful increase, further ruling out the alternative explanation.

IV. Substituting the bonds capital with other types of debt

If municipalities could switch away from bonds to other sources of capital, and if the costs of these alternate sources do not increase in response to the pollution, the higher costs of bonds would not influence their financing. Though banks are one such source (Bergstresser and Orr, 2014), they not only account for just 10–20% of the total debt of less populous municipalities and 5–10% of larger local governments, but also bank debt of municipalities may limit their ability to issue public debts in the future, as bank debts almost always have shorter maturity and higher priority than bonds which dilutes the claims of bond holders (Ivanov and Zimmermann, 2019).

6 Conclusion

This paper examines the causal link between pollution and municipal finance using the unexpected discovery of the PFAS contamination in 2016 in more than 200 U.S. counties. Using this close-to-exogenous event in a difference-in-differences setting comparing the municipalities in bordering counties, the paper finds that pollution makes new municipal borrowings expensive and in turn affects the local economy adversely due to a subsequent decline in public employment and municipal expenditure. A heightened risk to municipalities appears to be the reason behind the higher costs.

Interestingly, the burden of pollution falls not only on the municipalities dealing with the industry linked to the pollution, but rather on all the municipalities economically linked to the polluted area. Even the general obligation bonds, which are fiscally the most important and account for the largest share of municipal borrowing, are experience increased cost. It is also surprising that while municipal issuers enjoy varying levels of support from the federal and state governments, and while they are generally considered safe, their borrowing costs from the bond markets are susceptible to local pollution shocks.

It may also be useful to highlight the unique challenges surrounding pollutants such as the PFAS, which belong to a class of chemicals known as emerging pollutants. Unlike conventional pollutants, which are regulated and monitored for, the emerging pollutants pose unique challenges for the economy and the municipalities because absence of regulations makes recovering remediation costs of contamination through legal means difficult. At the same time, their adverse health effects materialize as soon as they contaminate the environment, and thus municipalities, which are the hyperlocal public good providers, end up shouldering the financial burden.

In the end, it is worth noting that other countries too have begun to discover PFAS contamination (Ao et al., 2019), and the consequences for less developed countries may be different and perhaps severe, since the capabilities to research emerging pollutants are concentrated in the developed countries (Bouwman, Wong, and Barra, 2012).

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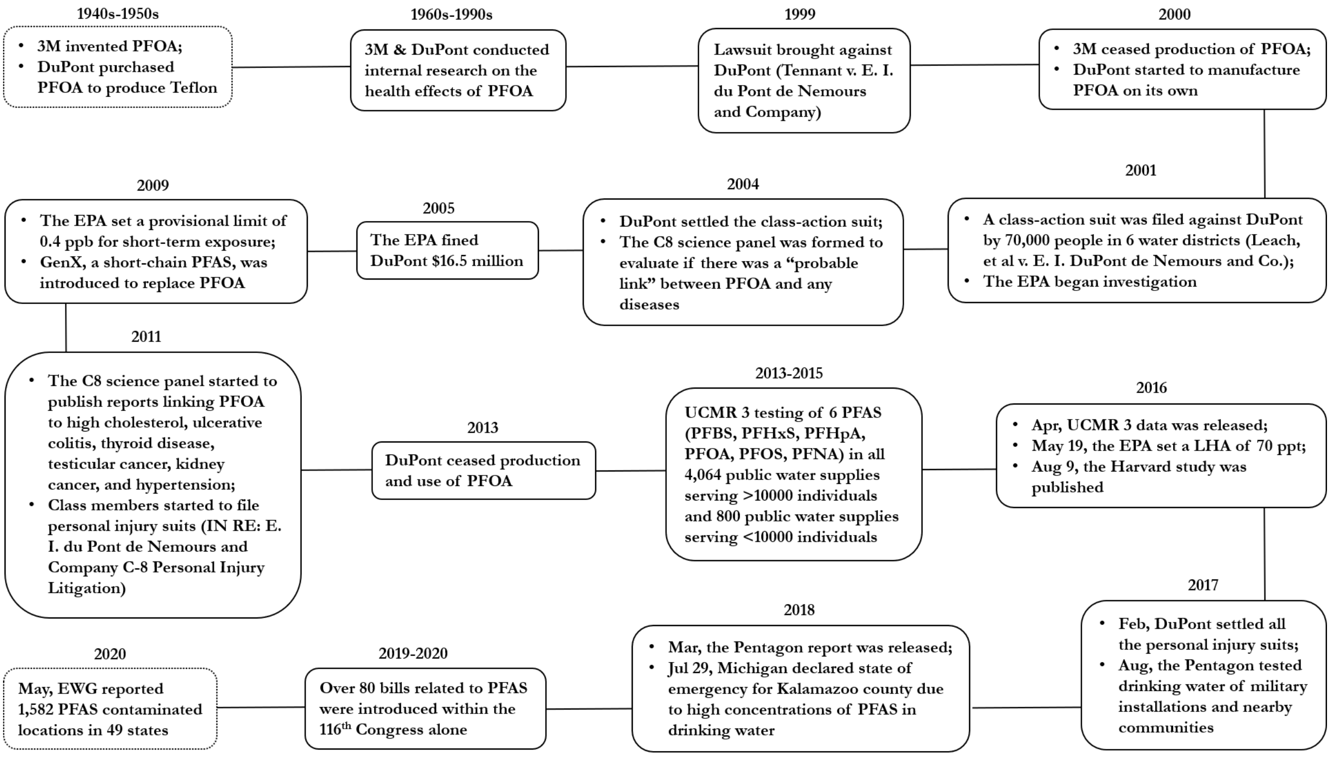
Figure I: Important Events surrounding PFAS

This figure shows major PFAS-related developments in the U.S. from 1940 till 2020.



Information adapted from Rich (2016, Jan. 6) and Soechtig and Seifert (2018), and two court cases, In re E. I. Du Pont De Nemours & Co. C-8 Pers. Injury Litig. (2019) and Leach v. E. I. du Pont de Nemours and Company (2014).

Figure II: Illustration of Treatment and Control Counties

This figure shows on the map of the U.S. the counties that were revealed to have PFAS in drinking water in the EPA's UCMR 3 testing data (*treated counties*) and the bordering but unpolluted same-state counties (*control counties*).

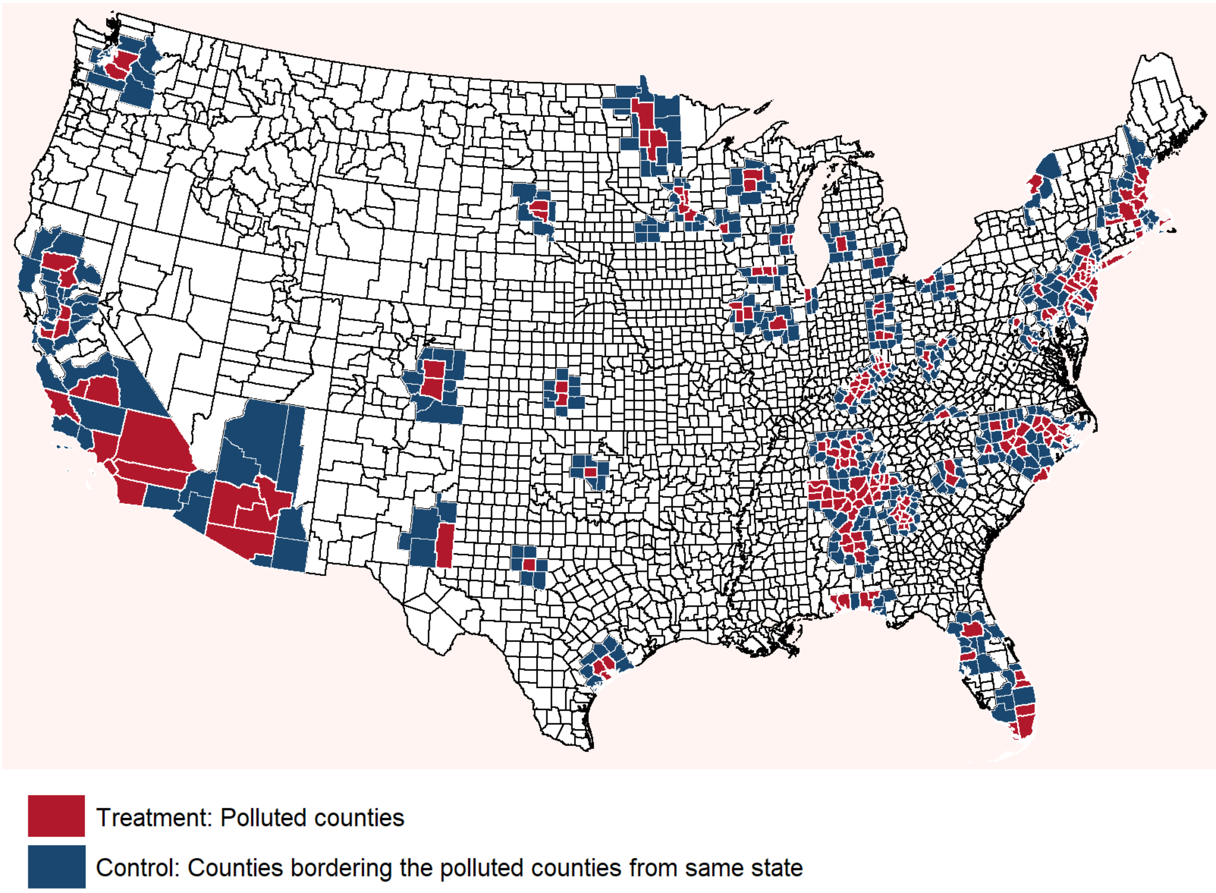
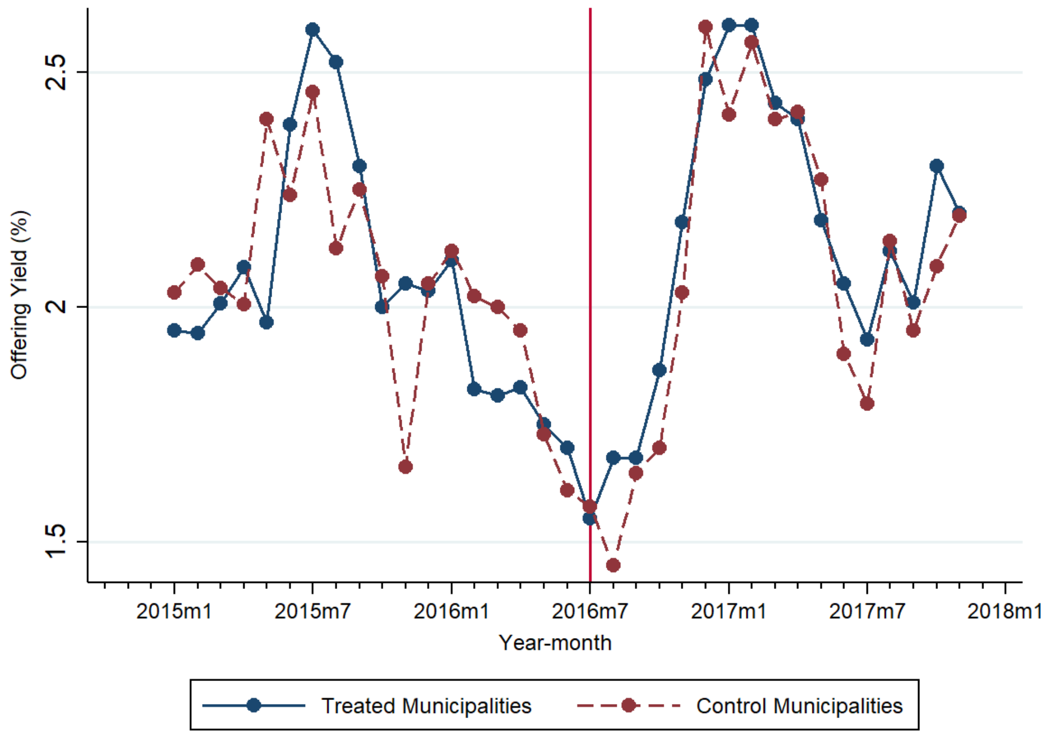


Figure III: Parallel Trends

This figure plots the offering yields of new, non-insured, general obligation bonds with maturity longer than 1 year issued by all municipalities from the treated (polluted) and control (bordering and unpolluted same-state) counties. The yields are aggregated to the month level. Panel (A) shows the median offering yields, whereas Panel (B) mean offering yields.

Panel A: Mean Offering Yields



Panel B: Median Offering Yields

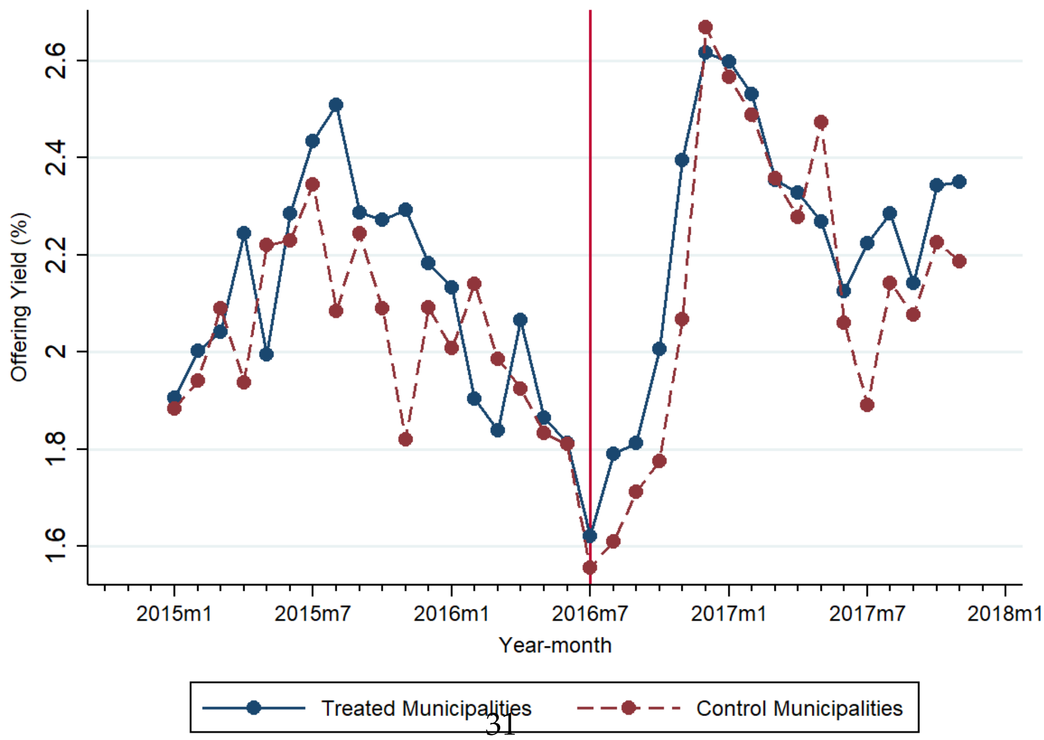
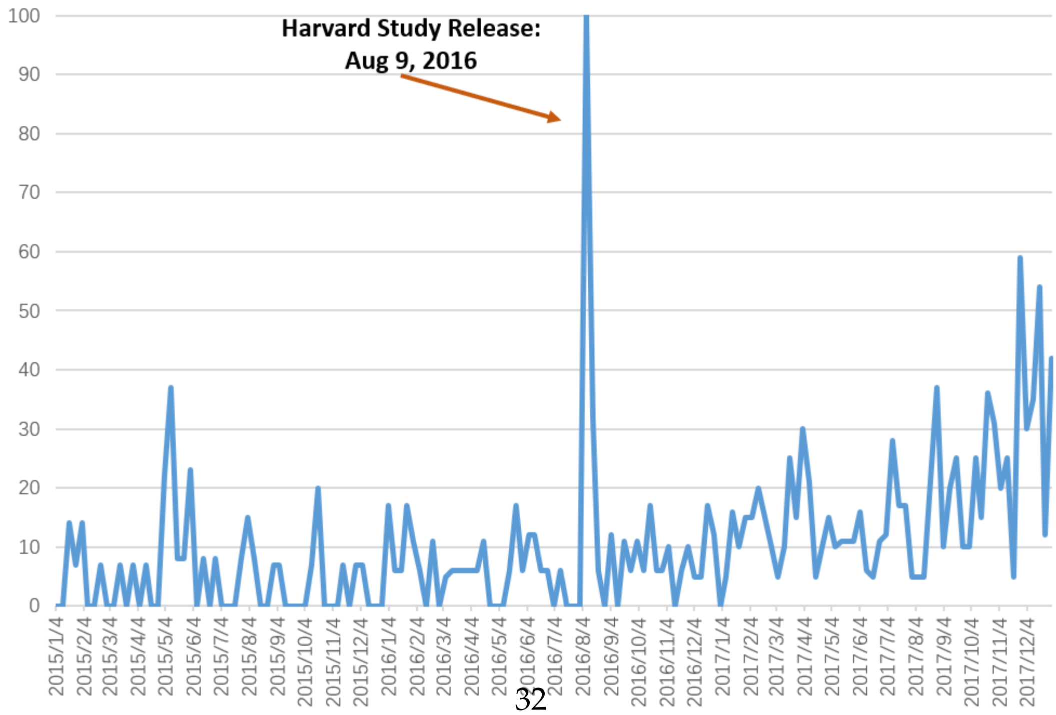


Figure IV: The Event

This figure illustrates the timing of the event. Panel (A) of the figure shows the publication of the findings of (Hu et al., 2016) in the Harvard Gazette (The Harvard Gazette, Aug 9, 2016). Panel (B) of the figure plots the Google Search Interest over time for the term "PFAS" in the U.S. from Jan 2015 to Dec 2017. Panel (C) of the figure shows the average Google Search Interest for the keyword "PFAS" for the contaminated and uncontaminated states. The contaminated states refer to the 33 states mentioned in Hu et al. (2016). The averages were calculated every half-year for the two set of states using the Google Trends data that was obtained semiannually from 2015 to 2017 for the state-level search interest related to the keyword. The arrows in the plot indicate the relative search interest in the contaminated states vis-à-vis the uncontaminated, whereas the vertical dashed line represents the timing of the event.

Panel A: The Harvard Gazette article

Panel B: Google Search Interest for keyword PFAS



Panel C: Difference in PFAS Search Interest between Contaminated and Other States

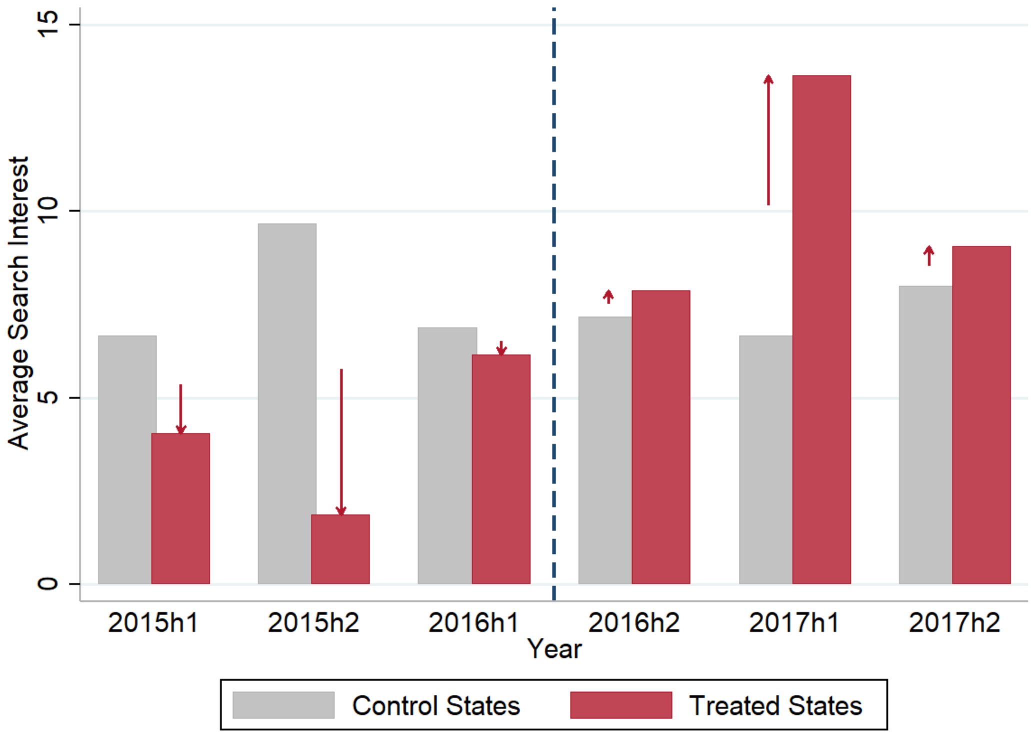


Figure V: Increase in Municipal Bond Yields due to Various Factors

This figure shows the effects on municipal bond yields of various factors found by other studies. The effect is measured in basis points with respect to a change in the factor mentioned on the x-axis. The definition of yields varies across studies. See Cornaggia et al. (2021, Table 2 Panel B), Gao et al. (2020, Page 454), W. Li and Zhu (2019, Page 2), Painter (2020, Table 3 Panel B: 16.1 bps multiplied by the climate risk standard deviation of 0.35 is 5.6 bps), Chava, Malakar, and Singh (2020, Table 3 Panel B), Gao et al. (2019, Table 5), and Goldsmith-Pinkham et al. (2020, Page 2).

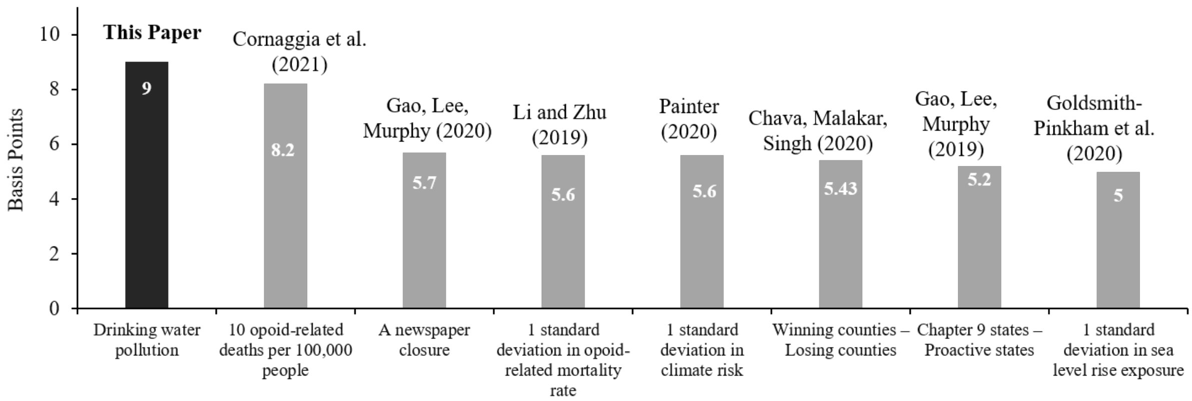


Figure VI: Location of Airports in the U.S. by the ARFF Index

This figure shows the locations of 420 Part 139-certified airports in the U.S. according to their Aircraft Rescue and Fire Fighting (ARFF) index as of October 2016.

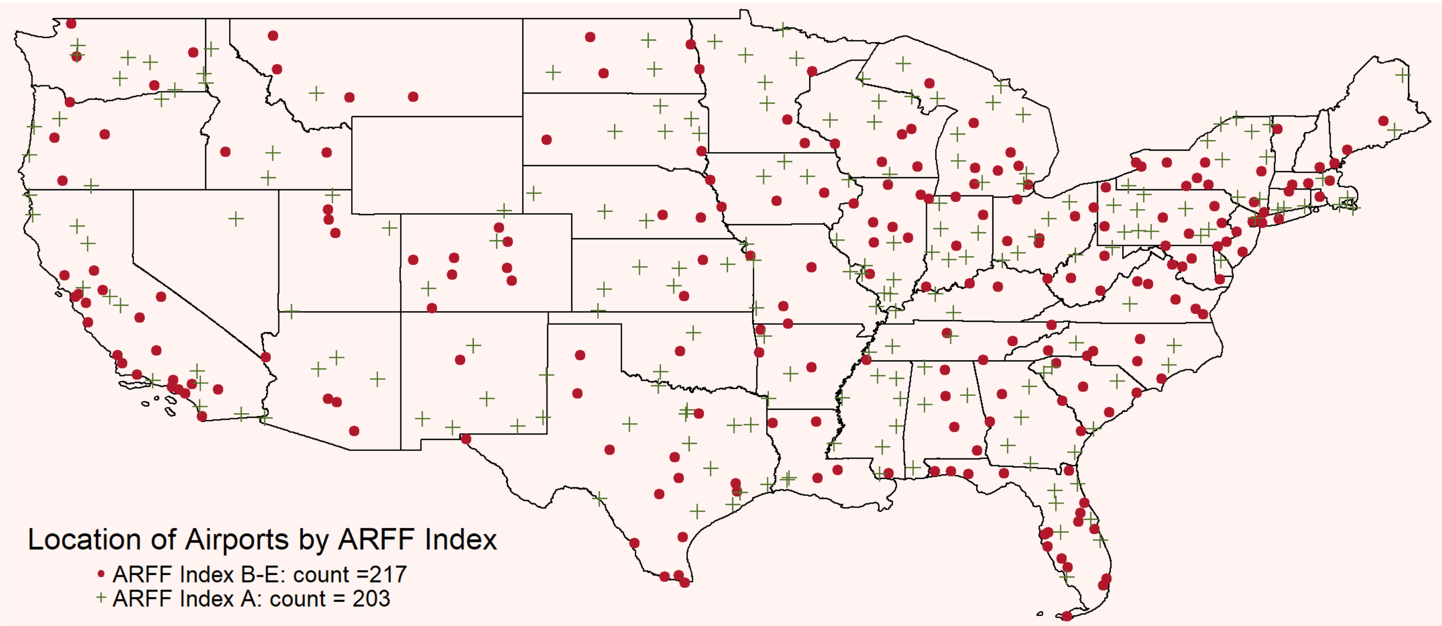


Table I: Summary Statistics

Panel (A) of this table shows the number and percent of detected polluted counties and concentration-level summary statistics for our regression sample. *N* indicates the number of counties detected PFAS and with PFOA, PFOS, PFHpA, PFHxS, PFNA, or PFBS having the highest concentration. In total, 103 counties detected at least one of the six PFAS chemicals. MRL is the UCMR 3 minimum reporting level. Concentrations and MRLs are in ng/L.

Panel A: Summary Statistics for PFAS Detection

	Detection in Counties		Concentration Statistics (ng/L)				
	N	Affected (%)	Mean	SD	Min	Max	MRL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PFOA	84	68.29	54.88	68.74	20	349.00	20
PFOS	73	59.35	201.70	310.73	40	1800.00	40
PFHpA	61	49.59	25.69	22.75	10	86.91	10
PFHxS	48	39.02	171.38	182.00	32	730.00	30
PFNA	13	10.57	37.51	10.75	27	55.88	20
PFBS	5	4.07	124.00	24.08	100	150.00	90

Table I: Summary Statistics (Continued)

Panel (B) of this table shows the municipal finance descriptive statistics for the treatment group, the control group, and for all combined for the period from 2015 to 2017. *Off. Yld.* is the offering yield expressed as percentages. *Coupon* is also measured in percentages. *Issue Amt* is the dollar amount issued in millions. *Tenure* is the original bond maturity in months. *Issue Rating* is the S&P's rating converted to a numeric scale. We assign the AAA rated bonds the value of 21 and the unrated 1. *Tax Exempt* and *Insured* are dummy variables each taking the value of 1 if the bond is federal tax exempt or insured and 0 otherwise, respectively. *Yld. Sprd.* is the spread between the bond's transaction yield and the yield on a maturity-matched treasury bond, calculated using investor transactions. *Monthly Trades* is the bond's number of secondary market transactions in a month. *Monthly SD of Price* is the bond's monthly standard deviation of transaction prices. Δ *County GDP* is the annual growth rate of the county gross domestic product. Δ *Income Per Capita* is the annual growth rate of the per person income at the county level. *Property Taxes* and *Intergov't Rev* are county-level aggregates for property taxes and intergovernmental revenues in millions.

Panel B: Summary Statistics for Municipal Bonds

	Full Sample				Control Group (C)				Treatment Group (T)			
	N	Mean	SD	Med	N	Mean	SD	Med	N	Mean	SD	Med
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Off. Yld. (%)	84687	2.16	0.95	2.13	39088	2.16	0.94	2.13	45599	2.17	0.97	2.13
Issue Amt. (mn)	84601	4.21	16.60	0.94	39061	4.61	15.97	0.91	45540	3.87	17.12	0.95
Coupon (%)	84842	3.50	1.24	3.39	39169	3.50	1.25	3.38	45673	3.50	1.24	3.40
Tenure (months)	84853	115.62	80.10	103.00	39175	116.50	80.76	103.00	45678	114.87	79.52	103.00
Issue Rating	84843	13.00	8.52	18.00	39168	13.01	8.43	18.00	45675	12.99	8.59	18.00
Tax Exempt	84853	0.93	0.25	1.00	39175	0.93	0.26	1.00	45678	0.94	0.24	1.00
Insured	84853	0.13	0.33	0.00	39175	0.13	0.34	0.00	45678	0.12	0.33	0.00
Yld. Sprd. (%)	829541	0.21	0.90	0.12	383191	0.19	0.89	0.11	446350	0.23	0.92	0.12
Monthly Trades	852565	7.39	16.80	4.00	394953	7.72	17.54	4.00	457612	7.10	16.14	4.00
Monthly SD of Price	792877	0.69	0.62	0.58	368124	0.69	0.63	0.58	424753	0.69	0.62	0.58
Δ County GDP	908	0.03	0.04	0.04	567	0.03	0.05	0.04	341	0.04	0.04	0.04
Δ Income Per Capita	908	0.03	0.02	0.03	567	0.03	0.03	0.03	341	0.03	0.02	0.03
Property Taxes (mn)	880	438.70	1845.91	103.31	546	355.12	2088.84	73.39	334	575.31	1350.20	228.60
Intergov't. Rev. (mn)	880	399.63	1274.62	105.12	546	305.10	1400.33	70.01	334	554.16	1020.09	238.05

Table II: PFAS Contamination and Offering Yields

This table reports the estimated treatment effects of pollution on offering yields of bonds from all, general-purpose, and special-purpose municipalities. General-purpose municipalities include county/parish (11), city/town/village (12), and local authority (16), whereas special-purpose municipalities include college or university (13), district/board of education (14), and direct issuer (21). The numbers in parentheses refer to the *issuer type code* in the SDC database. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs}$ $\times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. Columns (1) and (2) present the estimates for the whole sample. Columns (3) and (4) present the estimates for general-purpose municipalities. Columns (5) to (6) present the estimates for special-purpose municipalities. All regressions include issuer fixed effects and State × Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	All Municipalities		General Purpose		Special Purpose	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.06**	0.05***	0.09***	0.08***	0.03	0.02
	(2.24)	(2.71)	(2.82)	(3.40)	(0.63)	(0.63)
Bond & County Controls	×	✓	×	✓	×	✓
Issuer FE	✓	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓	✓	✓
R^2 (Adj)	0.25	0.87	0.25	0.86	0.26	0.87
Observations	73139	72345	46251	45902	26887	26442

Table III: PFAS Contamination and Offering Yields: By Repayment Obligation

This table reports the estimated treatment effects of pollution on offering yields for water revenue bonds, general obligation (GO) bonds, and other revenue bonds. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} + \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs} \times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for water revenue bonds, (3) and (4) for GO bonds, and (5) and (6) for other revenue bonds. All regressions include issuer fixed effects and State × Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Rev. (Water)		GO		Rev. (Other)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.48***	0.29*	0.10***	0.08***	-0.08	0.09
	(4.04)	(1.69)	(2.91)	(2.99)	(-0.80)	(1.07)
Bond & County Controls	×	✓	×	✓	×	✓
Issuer FE	✓	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓	✓	✓
R^2 (Adj)	0.22	0.87	0.25	0.87	0.24	0.85
Observations	2292	2204	39596	39369	4324	4290

Table IV: PFAS Contamination and Offering Yields: By Bond Maturity

This table reports the estimated treatment effects of pollution on offering yields of municipal bonds with different maturity. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs} \times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for bonds which mature in more than 15 years. Columns (3) and (4) present the estimates for bonds which mature in less than or equal to 15 years. All regressions include issuer fixed effects and State × Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	> 15 Yrs		≤ 15 Yrs	
	(1)	(2)	(3)	(4)
Treat × Post	0.13***	0.13***	0.08***	0.08***
	(3.32)	(3.31)	(2.70)	(3.15)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.64	0.76	0.23	0.88
Observations	8185	8033	38011	37815

Table V: PFAS Contamination and Offering Yields: Counties with Ex-ante High vs Low Debt Burden

This table reports the estimated treatment effects of pollution on offering yields of bonds from high-debt-burden counties vis-á-vis low-debt-burden counties. A county is considered as having high debt burden if its debt-to-revenue ratio in the pre-event year 2015 was higher than the cross-sectional median taken across all the sample counties in that year; and as having low debt burden otherwise. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs}$ $\times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for bonds of issuers from high-debt-burden counties. Columns (3) and (4) present the estimates for bonds of issuers from low-debt-burden counties. All regressions include issuer fixed effects and State $\times$ Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	High Debt Burden		Low Debt Burden	
	(1)	(2)	(3)	(4)
Treat × Post	0.10*	0.10***	0.10**	0.07*
	(1.97)	(3.32)	(2.37)	(1.75)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.24	0.85	0.25	0.88
Observations	21948	21887	23803	23767

Table VI: PFAS Contamination and Offering Yields: Ex-ante High vs Low Credit Risk Municipalities

This table reports the estimated treatment effects of pollution on offering yields of bonds from low-rated issuers vis-á-vis high-rated issuers. An issuer is considered as having high credit ratings if its rating in the pre-event year 2015 was higher than the cross-sectional median taken across all the issuers in that year; and as having low credit ratings otherwise. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs} \times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for low-rated issuers. Columns (3) and (4) present the estimates for high-rated issuers. All regressions include issuer fixed effects and State $\times$ Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	High Credit Risk Group		Low Credit Risk Group	
	(1)	(2)	(3)	(4)
Treat $\times$ Post	0.20***	0.11***	0.02	0.05*
	(3.58)	(2.68)	(0.53)	(1.66)
Bond & County Controls	$\times$	✓	$\times$	✓
Issuer FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.27	0.87	0.21	0.86
Observations	18120	17996	23813	23618

Table VII: PFAS Contamination and Offering Yields: By State Policies for Local Government Bankruptcy

This table reports the estimated treatment effects of pollution on offering yields of bonds from states with different policies for local government bankruptcy. The regression specification follows Equation (2):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{st} + \varepsilon_{imcst}$$

The outcome variable is the offering yield in percentage points for bond i of municipality m in county c of state s at time t. Treatment$_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; Post$_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with Treatment$_{cs}$ $\times$ Post$_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. Bond Controls$_{imcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for states which allow local government bankruptcy. Columns (3) and (4) present the estimates for states which does not allow local government bankruptcy. All regressions include issuer fixed effects and State $\times$ Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Bankruptcy Allowed		Bankruptcy Disallowed	
	(1)	(2)	(3)	(4)
Treat $\times$ Post	0.11*	0.11***	0.09*	0.07*
	(1.97)	(3.25)	(1.87)	(1.71)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.28	0.85	0.24	0.86
Observations	13116	13059	18911	18663

Table VIII: Real Effects of Pollution

Panel (A) of this table reports the estimated treatment effects of pollution on local public finance by government type. Following the Census Bureau classification, municipal (2) and township (3) governments are referred to as general-purpose local governments. Special district (4) and school district (5) governments are referred to as special-purpose local governments. The numbers in parentheses indicate the *government type codes* defined by the Census Bureau. The regression specification is:

$\text{Expenditure}_{mcst} = \beta_0 + \beta_1\ \text{Treatment}_{cs} \times \text{Post}_t + \beta_2\ \text{Revenue}_{mcst} + \alpha_{mcs} + \gamma_t + \varepsilon_{mcst}.$ See Eq (3).

Here m denotes local governments. In the left panel, the dependent variables are nominal dollar amounts scaled by the population to which the respective local government primarily serves. Total Revenue_{mcst} is per capita revenue. In the right panel, the dependent variables are in total current dollars. Total Revenue_{mcst} is total revenue. Special districts and school districts are areas unrelated to specific population concentration and hence population data are not available. The precise definition for each dependent variable is in Table (A.1). All regressions include government fixed effects and year fixed effects. Standard errors are clustered by government entity. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Changes in Local Government Expenditures

General-purpose				Special-purpose			
Dependent Variable	DID	N	R^2 (Adj)	Dependent Variable	DID	N	R^2 (Adj)
	(1)	(2)	(3)		(4)	(5)	(6)
Direct General Expenditure	–37.19*	4820	0.96	Direct General Expenditure	1.54***	16545	1.00
	(–1.73)				(2.87)		
Education Capital Outlay	–14.50*	4820	0.51	Education Current Expenditure	1.77***	12452	1.00
	(–1.75)				(4.19)		
Health Current Expenditure	–3.36**	2858	0.99	Total Debt Outstanding	4.63***	16545	0.99
	(–2.13)				(2.71)		
Hospital Total Expenditure	–5.70**	4820	0.99	Long-term Debt Issued	4.54**	16545	0.56
	(–2.56)				(2.50)		
Water Utility Total Expenditure	10.72**	4820	0.83				
	(2.15)						
Water Utility Construction	5.96**	4820	0.60				
	(2.12)						

Table VIII: Real Effects of Pollution (Continued)

Panel (B) shows the estimated treatment effects of pollution on county public employment. The regression specification follows Equation (4):

$$\text{Public Employment}_{cst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \text{ County Controls}_{cst} + \alpha_{cs} + \gamma_{st} + \varepsilon_{cst}.$$

Public Employment$_{cst}$ refers to the full-time equivalent public employment in county c of state s in year t. County Controls$_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). All regressions include county fixed effects and State $\times$ Year fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel B: Changes in Local Public Employment

	Log(1+ Public Employment)		$\frac{\text{Public Employment}}{\text{Total Employment}}$	
	(1)	(2)	(3)	(4)
Treat $\times$ Post	-0.39***	-0.31***	-0.02***	-0.02***
	(-4.36)	(-3.51)	(-5.02)	(-3.99)
County Controls	$\times$	✓	$\times$	✓
County FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.89	0.90	0.72	0.73
Observations	1400	1289	1400	1289

Table IX: Pollution Signal or Other Confounding County Attributes?

Panel (A) of this table reports the estimates of pollution effects on offering yields from an alternative empirical approach based on issuer's distance to a known PFAS-polluter—airports that have an Aircraft Rescue and Fire Fighting (ARFF) index of B–E. These airports, but not the ones with the index of A, are mandated to use PFAS-based Aqueous Film-forming Foams (AFFF) as firefighting agents. Panel (A) shows their polluting nature by regressing the following spatial autoregressive model from Equation (5):

$$\text{PFAS Contamination}_z = \beta_0 + \beta_1 \text{ Polluting Airport}_{z\leq 20} + \lambda \ \mathbb{W} \times \text{PFAS Contamination}_z + \varepsilon_z$$

Here z denotes zip codes. *Polluting Airport*$_{z\leq 20}$ is a dummy variable equal to 1 if there is a polluting airport within 20 miles of zip code z and 0 if a non-polluting airport. $\mathbb{W} \times Pollution_z$ is the spatially lagged dependent variable added to allow for the inference to be robust to the spillover of pollution among neighboring zip codes. The spatial weighting matrix $\mathbb{W}$ is based on queen contiguity. The outcome variable *PFAS Concentration* in Column (2) and *PFOA Concentration* in Column (3) are measured in ng/L. Equation (5) is fit with a generalized spatial two-stage least square estimator. z-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: PFAS Contamination around Different Types of Airports

	Pollution Dummy	PFAS Concentration	PFOA Concentration
	(1)	(2)	(3)
Polluting Airport	0.013*	11.860**	1.103**
	(1.660)	(2.349)	(2.000)
Spatially Lagged Dependent Variable	✓	✓	✓
R^2 (Pseudo)	0.013	0.003	0.001
Observations	4924	4924	4924

Table IX: Pollution Signal or Other Confounding County Attributes? (Continued)

Panel (B) shows the differential impacts of the pollution discovery on issuers near polluting airports and on those near non-polluting ones. The regression specification is from Equation (6):

$\text{Off Yld}_{ijcst} = \beta_0 + \beta_1 \text{ Post}_t + \delta \text{ Bond Controls}_{ijcst} + \alpha_{jcs} + \gamma_{st} + \varepsilon_{ijcst}$.

All variables are defined in Table (I). All regressions include issuer fixed effects and *State* $\times$ *Year* fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel B: Offering Yield Increase around Airports

	Polluting Airport in 20 miles		Non-polluting Airport in 20 miles	
	(1)	(2)	(3)	(4)
Post	0.16***	0.17***	0.10**	0.08**
	(4.16)	(5.45)	(2.03)	(2.20)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.25	0.86	0.25	0.89
Observations	56387	55190	18646	18321

Table X: PFAS Contamination and Offering Yields: By Bond's Bank Qualification

This table reports the estimated treatment effects of pollution on offering yields of bank qualified bonds and bank not-qualified bonds. The regression specification follows Equation (2):

$$\text{Off Yld}_{ijcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{ijcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{jcs} + \gamma_{st} + \varepsilon_{ijcst}$$

The outcome variable is the offering yield in percentage points for bond i of public issuer j in county c of state s at time t. $Treatment_{cs}$ equals 1 if the drinking water supply of county c of state s was detected to have PFAS in the UCMR 3 data and 0 otherwise. t spans 2015 through 2017; $Post_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with $Treatment_{cs} \times Post_t$ captures the change in the dependent variable before and after the event in treated counties relative to bordering control counties in the same state. $Bond\ Controls_{ijcst}$ include the bond's issuance amount, coupon rate, tenure, tenure inverse, the S&P rating of the issue, whether the bond is tax exempt, and whether the bond is insured; $County\ Controls_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Columns (1) and (2) present the estimates for states which allow local government bankruptcy. Columns (3) and (4) present the estimates for states which does not allow local government bankruptcy. All regressions include issuer fixed effects and $State \times Year$ fixed effects and cluster standard errors by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Not Bank Qualified		Bank Qualified	
	(1)	(2)	(3)	(4)
Treat × Post	0.10***	0.10***	0.06	0.04
	(2.65)	(2.95)	(1.52)	(1.43)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.23	0.85	0.23	0.92
Observations	32899	32651	12789	12690

Table XI: PFAS Contamination and Yield Spreads

This table reports the estimated treatment effects of pollution on municipal bond's trading yield spreads. The regression specification follows Equation (7):

$$\text{Yld Sprd}_{ijcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Control}_{ijcst} + \delta_2 \text{ County Controls}_{cst} + \alpha_{ijcs} + \gamma_{st} + \varepsilon_{ijcst}$$

The outcome variable is the monthly volume-weighted sum of a bond's transaction spreads, which are the spread between the trading yield and the same-date linearly interpolated yield on a maturity-matched treasury bond. The estimates are presented in the order of that for transactions between dealers and customers, water revenue bonds, GO bonds, other revenue bonds, issuers with ex-ante low credit ratings, and issuers with ex-ante high credit ratings. All regressions include bond and county controls, CUSIP fixed effects, and $State \times Year$ fixed effects. $Bond\ Control_{ijcst}$ include the time to maturity in months, time to maturity inverse, standard deviation of transaction prices, and number of trades at the bond-month level. $County\ Controls_{cst}$ include the GDP growth rate, per capita income growth rate, property taxes, and intergovernmental revenue at the county-year level. All variables are defined in Table (I). Standard errors are double clustered by CUSIP and month. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	All Bonds	Rev. (Water)	GO	Rev. (Other)	High Debt Burden	Low Debt Burden
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.10***	0.14***	0.09***	0.12***	0.13***	0.10***
	(3.65)	(4.31)	(3.33)	(4.10)	(4.15)	(3.71)
Bond & County Controls	✓	✓	✓	✓	✓	✓
CUSIP FE	✓	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓	✓
Cluster (CUSIP, Month)	✓	✓	✓	✓	✓	✓
R^2 (Adj)	0.78	0.73	0.77	0.78	0.79	0.77
Observations	362984	27966	247381	87636	128973	233421

A Data Appendix

The key data that allows us to link the municipalities with their location information come from SDC Global Public Finance database. It includes information on 6-digit CUSIP, issuer name, type, and location. Using a combination of name matching algorithm and manual linking, we merge county names in the SDC data with the Federal Information Processing Standard (FIPS) county codes. 6-digit CUSIP code is the primary linking variable, using which we match the municipality location with their bond issuance data from Thomson Reuters Eikon and their trade data from MSRB.

Then the PFAS monitoring data come from UCMR 3. The data contain the detection level for the six PFAS for each of the public water systems monitored. Using the zip code of the water systems and the HUD's USPS zip code crosswalk files, we aggregate the PFAS data to the county level to identify whether a county is contaminated, i.e. if any of the zip codes within a county's boundary was detected to have any of the six PFAS, the county is considered contaminated. Since we measure PFAS contamination at the county level, we disregard municipalities which cannot be linked to a county, who operate in multiple counties, and those who have a non-U.S. location.

We link the above two data using county FIPS, and then use county adjacency information from the Census Bureau to identify the counties bordering the contaminated counties. We focus only on those municipalities that issued bonds at least once before and after the event. Spanning 2015 to 2017, the final data consists of 61,075 bonds (at the CUSIP level) issued by 1,210 municipalities in the treated group and 52,138 bonds issued by 981 municipalities in the control group. Similarly, the secondary market data cover 25,881 bonds issued by 2,580 municipalities in the former group and 22,115 bonds by 2,147 in the latter.

Finally, we collect the airport ARFF index data from the FAA as of October 2016 (close to the event, Aug 2016) and link it with PFAS contamination data using zip codes.

Table A.1: Government Finance Variable Definitions

This table presents the definitions of and Census Bureau item codes for government finance variables. For expenditure, the capitals in parentheses are object codes that represent character categories and the numbers are function codes. For indebtedness, the alphanumericals in parentheses are debt classification codes.

Direct General Expenditure	All expenditures except intergovernmental, utility, or liquor store expenditures. More specifically, it includes expenses on current operations (E), interest on debt (I), assistance and subsidies (J), capital outlays on construction (F) and other than construction (G), social insurance trust expenditures on public employee retirement systems (X) and all other social insurance trust systems (Y)
Education Capital Outlay	Direct general expenditures to build long-term assets (F) and purchase long-term assets (G) for elementary and secondary education (F12 and G12), higher education (F16, F18, G16, and G18), and other education (F21 and G21)
Education Current Expenditure	Direct general expenditures used to pay employees, purchase supplies and hire contractors (E) for elementary and secondary education (E12), higher education (E16 and E18), and other education (E21)
Health Current Expenditure	Current expenditures for the conservation and improvement of public health (E32), other than hospital care
Hospital Total Expenditure	The sum of direct (E, F, G) and intergovernmental (L, M) expenditures for hospitals (E36, F36, G36, L36, and M36)
Water Utility Total Expenditure	The sum of direct (E, F, G, I) and intergovernmental (L, M) expenditures for water utilities (E91, F91, G91, I91, L91, and M91)
Water Utility Construction	Expenses on the production, additions, replacements, or major structural alterations to water utility fixed works, undertaken either on a contractual basis by private contractors or through a government's own staff (F91)
Total Debt Outstanding	End of fiscal year total debt outstanding (44T, 49U, 64V)
Long-term Debt Issued	Long-term debt issued (24T, 29U)