Polluted Waters and Municipal Finance*

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Abstract

We show that pollution increases the offering yields of municipal bonds, indicating increased risk. We establish this using a difference-in-differences design, comparing the bonds from 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 greater for riskier bonds characterized by repayment obligation, *ex-ante* debt burden, unrated issuance, maturity, and bankruptcy access. The resulting pollution-related investment needs and a reduction in public sector employment and expenditure likely underlie the risk. An instrumental variable-like method utilizing airports as a potential contamination 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 they who plan, build, and maintain public infrastructure and deliver public goods and services at the hyperlocal level. 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), and 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).

The goal of this paper is to examine whether pollution affects the borrowing costs (bond yields) of 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 unmonitored contaminants. Public sector employment and expenditure subsequently shrank, adversely affecting the local economic risk and likely contributing to the increased yields.

While municipal borrowing has been shown to be affected by 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 emerged from the nationwide testing of drinking water in the U.S. under a program called third Unregulated Contaminant Monitoring Rule (UCMR 3). The drinking water supplies of 201 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, and it received widespread publicity (The Harvard Gazette, Aug 9, 2016; Hu et al., 2016), causing Google searches for the keyword "PFAS" to surge massively. Therefore we utilize this event in our DID design. The treatment group consists of the municipal bonds from the polluted counties, the control group consists of 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 unwatched and unmonitored until the event. In fact, the UCMR (3), running from 2013 to 2015, was the first national-scale program to monitor 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 prior.[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,

[1] Sampling and analysis of PFAS require special precautions to avoid cross-contamination, and the best practice 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 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 was it discovered that they can seep into the environment, including ground and drinking water. They are also incredibly resistant to environmental degradation, and thus are known as the "Forever Chemicals". So while it is not well understood when and how some areas became contaminated, it is unlikely that the underlying processes, which may have spanned several decades, correlate with the financial characteristics of the municipalities.

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

since drinking water provision usually falls within geographic boundaries, e.g., counties. *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 general-purpose municipalities, but not of special-purpose ones, i.e., 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, it is just 2–3 bps (statistically insignificant). In economic terms, a 9-bps increase in offering yields of general-purpose municipalities is roughly equivalent to a 3.7-bps increase in annual property taxes or a $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 unlinked to pollution as they are somewhat shielded from fluctuations in the local (county-level) economic conditions due to various state and federal policies.[4] Thus the rest of our analyses focus on the general-purpose municipalities only.

[4] School districts receive significant revenues from state and federal governments and are subject to strict legal and regulatory oversight, and special districts often earn revenues through service charges (e.g., park usage fees). Thus the special-purpose municipalities are less tightly linked to the general economic growth than are the general-purpose municipalities.

To determine whether it is risk that pushes the offering yields higher, the next set of regressions evaluates how these yields changed in the sub-samples of bonds 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 municipalities with an *ex-ante* high and low tendency to issue unrated bonds; (iv) bonds from counties with an *ex-ante* high and low debt burden; and (v) bonds from states that allow municipalities to access the Chapter 9 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-sample than for the latter.

Notably, within the first classification scheme, the increase was a 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 need for cleanup and pollution-abatement investment, but also the GO bonds, whose repayments highly depend on economic conditions of the local area.

To 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 drinking water contamination than those within 20 miles of the other airports, offering us a credible proxy for the contamination. Then, we find that offering yields of the former municipalities increased by 16–17 bps after the event, statistically significant at the 1% level, whereas those of the latter increased by just 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 the increase in offering yields of local municipalities.

A fundamental question then arises: Which economic factors fueled the municipalities' risk that led to the higher bond yields? One factor appears to be the changing expenditure pattern of the general-purpose municipalities. Expenditure in the general category, education, and health *declined* in the polluted counties vis-à-vis the control, while expenditure on water infrastructure increased. Also, public sector 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 sector 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, listed in no particular order, have been shown to affect municipal bonds: the 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 roles (Garrett, 2021), corruption and political connection (Butler, Fauver, and Mortal, 2009), holdings 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 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 doctors' offices (Danagoulian, Grossman, and Slusky, 2020), and depleting housing stock and rising public expenditure (Christensen, Keiser, and Lade, 2019), while ground water contamination results in depressed house prices (Muehlenbachs, Spiller, and Timmins, 2015). We show that PFAS contamination of drinking water makes municipal borrowing expensive and reduces local municipal expenditure and public sector 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, perfluorooctanesulfonic acid (PFOA) and perfluorooctanoic acid (PFOS) were the first to be invented, have been manufactured the longest, and are understood the best. A wide variety of consumer products and industrial processes have 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 Environmental Protection Agency (EPA) as "contaminants of emerging concern", PFOA and PFOS are highly toxic and extremely soluble in water, and are currently being researched for adverse developmental, reproductive, and systemic 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 PFAS.[5]

[5] We do not attempt to describe the scientific advances in these chemicals and refer readers 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.

The Event: Revelation of PFAS Contamination

PFAS were never monitored on a large scale in drinking water supplies until the third Unregulated Contaminant Monitoring Rule (UCMR 3), under which monitoring took place across the U.S. from January 2013 to December 2015 (Federal Register, May 2, 2012, Exhibit 3: Timeline of UCMR Activities).[6] Relying on the data from the program, Hu et al. (2016) identified PFAS contamination, which made national headlines, such as in The Harvard Gazette (Aug 9, 2016), as 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 became contaminated, and while it must have occurred non-exogenously, we argue that the *information flow* to the market about the contaminated locations is "close to exogenous". First, 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] Second, predicting the locations before the program was implausible, as it would have needed 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

[6] The UCMR requires the 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, the 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] The 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 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, and then the mean was calculated within each interval for the two sets of states.

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

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 in investment and $3 million in yearly maintenance to install drinking water treatment equipment to remove GenX, a PFAS, in Brunswick county, North Carolina (National Association of Counties, Apr 15, 2019). The contamination may also lead to lost opportunities; e.g., the redevelopment plan of the 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 the 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 116th Congress (National Conference of State Legislatures, Jan 25, 2021), and a federal regulation concerning PFAS in drinking water is currently being drafted (Federal Register, EPA, Mar 10, 2020).

2 Empirical Research Design

We employ a DID design based on the detection of PFAS in drinking water under the UCMR (3) program: the treatment group consists of the counties with positive PFAS detection and the control group consists of the bordering counties that lie within the

[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 set 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 the affected residents with free 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). The 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 New York if a 10 parts per trillion (ppt) limit on PFAS were 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 lifetime advisory of 70 ppt for PFOA and PFOS individually or combined, New Jersey set the maximum contaminant level (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.).

same state but did not have PFAS contamination; August 9, 2016, serves as the event date. The sample consists of 123 treated counties and 210 control counties from across 30 states, as shown on the map of the contiguous U.S. in Figure (II).[11] Specifically, all the local governments, municipalities, and other public issuers within the treated counties are considered treated. This strategy to compare within-state bordering counties is a variation of the empirical strategy used in Huang (2008) and Dube, Lester, and Reich (2010), among others.

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

$$\text{Outcome}_{imcst} = \beta_0 + \beta_1\ \text{Treatment}_{cs} \times\ \text{Post}_t + \delta\ \text{Controls}_{imcst} + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst}\ , \quad (1)$$

where $Outcome_{imcst}$ is the offering yield of municipal bond i issued on date t by municipality m from county c of state s. $Treatment_{cs}$ 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_{sy} 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.

[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.

Is the TWFE an appropriate estimator in the current DID design?

A key issue with the TWFE estimator is that in *staggered* DID designs, it may aggregate individual treatment effects by assigning "negative weights" to some of them (Borusyak, Jaravel, and Spiess, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020). Since the estimator is the 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 rather 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' prevailing financial conditions, 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 the assumption is unverifiable, Figure (III) plots the trends of the 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 are parallel before the event. The slight increase in mean/median offering yields for the treated group after the event thus represents the treatment effect.[12]

[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, bond ratings and maturities, etc. Thus the plots may mask the true treatment effect, for which regressions provide robust estimates.

3 Data and Summary Statistics

We use three key pieces of data in this paper: PFAS contamination data from the UCMR (3) program; municipal bond issuance and trade data from Thomson Reuters Eikon and the 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 sector employment data from the Annual Survey of Public Employment & Payroll (ASPEP). Furthermore, data from the Federal Aviation Administration (FAA) on airport certification and locations are used in the instrumental variable-like method, and data from the Bureau of Economic Analysis (BEA) are used to capture local economic conditions.

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 the transaction. The steps to process and link these data are provided in the Data Appendix (Appendix A). The regression sample for new bonds consists of 45,678 bonds (at the CUSIP level) issued by 1,035 municipalities in the treated group and 39,174 bonds issued by 811 municipalities in the control group. Similarly, the sample for already-issued bonds consists of 23,263 bonds issued by 1,674 municipalities in the former group and 15,922 bonds by 1,382 municipalities in the latter.

The variable of interest is municipal bond yields. For new bonds, it is the *offering yield* (yield to maturity at issuance), and for already-issued bonds, the *monthly yield spreads*. To calculate the spreads, we first find the yield spread of each transaction as its trading yield minus the maturity-matched treasury yield (imputed using linear interpolation to the nearest month), and then average the transaction yield spreads over the month, weighted by the respective transaction amounts.[13]

Panel (A) of Table (I) shows key statistics of 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

[13] Owing to a lack of liquidity, if a bond trades less than five times in a year, it is excluded 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).

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) provides summary statistics for municipal bonds and counties' economic conditions. A typical newly issued municipal bond has an offering yield (yield to maturity at issuance) of 2.16%, coupon of 3.5%, maturity of 9.5 years, and S&P rating of BBB (equivalent to 13 on a numerical scale that has the value 21 for a AAA rating, 2 for a D, and 1 for an unrated bond). Treated bonds are slightly smaller ($3.87 million versus $4.61 million), 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 (23 bps versus 19 bps), and they trade less frequently (7.1 times per month versus 7.7 times per month). 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.

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:

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

where *Off. Yld.* is the offering yield of bond i (at CUSIP level) issued on date t by municipality m from county c of state s; 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 federal tax exempt and insured;

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

County Controls$_{cst}$ include rates of growth of county GDP and income per capita, and property taxes and intergovernmental revenues (in millions); and α_{mcs} is municipality fixed effects and γ_{sy} is "*State*×*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 an increase of 5–6 bps in offering yields relative to a municipality from a neighboring uncontaminated county after the revelation of the contamination. Since it is the general-purpose municipalities which depend the most on local economic conditions, as opposed to the special-purpose municipalities which 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 an increase of 8–9 bps (Columns 3 and 4), the latter saw no measurable effect (Columns 5 and 6). These estimates are robust to any time-invariant differences across municipalities and counties because of the municipality fixed effects, to state-specific annual trends due to "*State*×*Year*" fixed effects, and to a broad set of controls.

Regarding the effect of pollution on offering yields, our preferred estimate comes from the no-covariate specification in Column (3), that is, a 9-bps increase for the general-purpose municipalities. Since pollution largely affects only the general-purpose municipalities, not the special-purpose municipalities, in the remaining analysis, we focus only on the former.

Then the question arises, is a 9-bps increase in the offering yield economically large? This change is equivalent to a 4.3% increase over the average yields the affected general-purpose municipalities paid in 2016 (before the event). In present value terms, it represents $265 million more in interest costs.[16] If financed through annual property taxes, it would be equivalent to raising the taxes by 3.7 bps ($27 million interest payment as

[15] *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.

[16] These municipalities from the polluted counties borrowed $30 billion in bonds with an average maturity of 119 months in 2017. The 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 years in 2017 amount to about $265 million.

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 whether 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 versus 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 the bulk of public borrowing, are backed by the taxation 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 the 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. Thus we predict that the effect of drinking water pollution on offering yields should be strongest for the revenue bonds linked to water provision, moderate for the GO bonds, owing to their links with economic growth, and weakest for the other revenue bonds unrelated to water provision.

To test the above prediction, we estimate Equation (2) separately for the three groups and present the results 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 they 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 the local economy not just through directly linked (water) municipalities, but through all economically dependent municipalities, including the GO borrowers.

II. Long versus short maturity bonds

Longer-maturity bonds are riskier than those with a 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 the 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 results in Table (IV). Consistent with the risk explanation, longer-maturity bonds experienced a 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 an *ex-ante* higher debt burden have a 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. To calculate the debt burden of a county, we aggregate the debt (total debt outstanding) of all the sub-state municipalities—county, municipal, and township governments—in the county and divide it by their aggregated total revenues. 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 the high-debt-burden group otherwise. We examine the effect of pollution separately for the two groups using Equation (2) and present the results in Table (V). Consistent with the risk explanation, relative to the control, the treated municipalities in the *ex-ante* high-debt-burden counties experienced a larger increase (10 bps, Column 2) than those in the low-debt-burden group (7 bps, Column 4).

IV. Ex-ante high versus low tendency to issue unrated bonds

Bond credit ratings indicate the default risk of the issuing municipalities, and thus, the lower the rating is, the stronger would be the effect of pollution on offering yields. However, municipalities often tend to issue a mix of unrated and rated bonds, and even the bonds in the same issue will often have different credit ratings. Hence, relying on the bond ratings alone may misrepresent the municipal default risk. Moreover, unlike corporation ratings, the municipality ratings are updated irregularly and may fail to capture a change in risk that occurs over a short time horizon. We thus devise an intuitive and fast-updating measure that can be applied to even those municipalities that issue unrated bonds. The measure is defined as the ratio of the unrated bond issuance amount to the total issuance amount of a municipality in a year, and the larger this value, the higher the risk. Using this measure, we assign a municipality to the high-tendency group if its ratio in the pre-event year (2015) was greater than or equal to the cross-sectional sample average, and to the low-tendency group 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-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 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 versus without access to Chapter 9 bankruptcy

Municipalities from the states that allow access to the Chapter 9 Bankruptcy Code 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 sets of municipalities using Equation (2) and present the results in Table (VII). Consistent with the risk explanation, with respect to the control, the treated municipalities in the Chapter 9 states experienced a 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 Sector 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 sector employment using the same DID strategy.

Following an 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 separately compare municipal expenditure in the polluted counties with surrounding unpolluted counties for these two groups 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 the municipality and year fixed effects, respectively. $Post_t$ takes the value of 1 for $t > 2016$ and 0 otherwise. We explicitly control for revenues in these regressions, as expenditures likely depend on them. Also, the revenues and expenditures are expressed as *per capita* dollar amounts for the general-purpose municipalities and dollar amounts for the special-purpose municipalities, to which the concept of serviceable population, and hence per capita measure, does not apply. The definitions of expenditure categories are provided in Table (A.1). Finally, standard errors are clustered at the municipality level.

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

For brevity, we show the key coefficients collected from the individual regressions in Panel (A) of Table (VIII). For the general-purpose municipalities, the "DID" coefficients in Column (1) suggest that relative to the control, the 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. Thus the expenditures on water utilities appear 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, for the special-purpose municipalities, the "DID" coefficients in Column (4) suggest that their expenditure 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 a similar economic environment, the type affected by the pollution decreased expenditures, while the type unaffected increased them.

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

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

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 the natural log of public sector employment, and the coefficients suggest that the employment decreased by about 26–33% in the polluted counties vis-à-vis the unpolluted counties. Alternatively, the dependent variable in Columns (3) and (4) is the share of public sector employment in total employment, and this also dropped by about 2 percentage points. Overall, the effect of pollution on the public sector employment is economically large.

Taken together, the declining municipal expenditure and public sector employment appear to be the economic forces that likely contribute to the increased municipal risk.

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. The UCMR (3) program did not monitor most small public water systems, nor 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 (IV) 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 aqueous film-forming foams (AFFF), which primarily consist of PFAS (Part 139 Certification of Airports, 2004).[18] Further, for operational readiness purposes, the FAA requires the airports to test their firefighting equipment every 9 to 24 months (Federal Aviation Administration, 29 Oct 2019, 2020). Thus we classify those airports indexed B–E as *polluting* and those indexed A as *non-polluting*, as the former discharge PFAS into the ground regularly and have high potential to contaminate 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, not through other mechanisms. The restriction seems plausible since we restrict our focus

[18] Owing to their excellent petroleum-based fire suppression properties, AFFF are exceptionally suited for usage at airports, and that is probably why, despite their adverse health effects, the FAA mandated airports to use them in the past. The FAA has now initiated steps to minimize 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 for only 1 out of 521 (0.2%) certified airports.

only to the areas surrounding airports, with some surrounding *polluting* airports, while others, *non-polluting*.

We begin by estimating the following spatial autoregressive model using a generalized spatial two-stage least squares estimator to validate the proxy:[20]

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

where the dependent variable is a zip code-level contamination measure, and the sample includes all zip codes within 20 miles of the certified airports. *Polluting Airport*$_{z\leq 20}$ indicates the airport type around a zip code z; it is 1 for *polluting* type and 0 for *non-polluting*. $\mathbb{W}$ is a queen contiguity-based spatial weighting matrix whose elements take the value of 1 for bordering zip codes and 0 for others. The spatially lagged dependent variable, "$\mathbb{W}\times$ *PFAS Contamination*$_z$", accounts for the diffusion of pollution. Finally, the coefficient of interest, β_1, captures the direct effect of polluting airports on nearby areas.

Panel (A) of Table (IX) shows the results of the above regression for three dependent variables measuring contamination: whether a zip code z had 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, a polluting airport, when present within 20 miles of an area, leads to a 1.3% higher probability of contamination of drinking water (Column 1), 11.86 parts per trillion (ppt) more PFAS (Column 2), and 1.1 ppt more PFOA (Column 3). In effect, the ARFF B–E airports indeed predict the contamination, validating our proxy.[21]

[20] This model is needed to account for the spatially correlated nature of a contamination process. Water supplies of spatially closer areas are likely to become contaminated together, and the contamination could come both from the polluting airports (direct effect) and from neighboring areas which were first contaminated by the airports (indirect effect). Moscone, Knapp, and Tosett (2007) uses a similar model to study spatial variation in mental health expenditure.

[21] Other studies report similar conclusions, e.g., Ahrens, Norström, Viktor, Cousins, and Josefsson (2015) link the PFAS contamination around Arlanda airport in Sweden to its chemical usage, Høisæter, Pfaff, and Breedveld (2019) document ground water PFOS contamination due to AFFF usage at a Norwegian firefighting training facility, and Adamson et al. (2020) link AFFF usage at U.S. military installations to PFAS contamination of the surrounding areas.

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:

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

Panel (B) of Table (IX) shows the regressions results. We see that the municipalities near polluting airports witnessed an increase of 16–17 bps in offering yields (Columns 1 and 2), whereas those close to non-polluting airports experienced a far smaller increase of 8–10 bps (Columns 3 and 4). Thus, all general-purpose municipalities located close to an airport that are mandated to use PFAS saw greater increase in offering yields after the event than those closer to an airport that are not.

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 yields of the general-purpose municipalities.

5 Supplementary Discussion

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

I. Ameliorating effect of tax privileges

Given that bank-qualified municipal bonds offer special tax privileges for 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 on the bonds that are not bank qualified. We thus examine the effect of pollution separately for the two groups using Equation (2) and present the results in Table (X). Consistent with the ameliorating effect of tax privileges, bonds of affected municipalities that are not bank qualified saw a large increase of 10 bps relative to the bonds of the same type issued by the unaffected municipalities (Columns 1 and 2), whereas the bank-qualified bonds saw a much smaller increase of 4–6 bps, which is not statistically significant (Columns 3 and 4).

II. Effect on yield spreads of already-issued bonds

Although offering yields affect municipal borrowing costs, yield spreads of already-issued bonds reflect the views of investors on municipal risk, and thus the spreads should rise if they perceived that the pollution made the municipalities riskier. Another advantage of yield spreads analysis is that it allows us to observe the changes in investors' views about the same bond over time. We use the following regression equation:

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

where *Yld. Sprd.*$_{imcst}$ is the yield spread in month t of bond i of municipality m in county c of state s. The regression includes bond (CUSIP) fixed effects, α_{imcs}, and "*State*$\times$*Year*" fixed effects, γ_{sy}. While *County Controls*$_{cst}$ are the same as in Equation (2), *Bond Controls*$_{imcst}$ include the bond's remaining maturity at the time of the transaction (in months) and its inverse, the number of trades in each month, and monthly standard deviation of the bond's dollar transaction prices. Standard errors are double clustered by CUSIP and month.

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

III. Investors' preference for pollution-free investment

A capital-supply explanation for our findings could be that investors have a 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 a reduced supply of capital from such investors. Recall that longer-maturity bonds of the same municipalities experienced a larger increase than their shorter-term bonds. Had the increase been driven by the preference for pollution-free investment, bonds of all maturities of the affected municipalities would have experienced a similar increase, and the special-purpose municipalities from the polluted counties too would have suffered this increase. However, the findings suggest otherwise and rule out this explanation.

IV. Substituting bond capital with other types of debt

Municipalities' financing would remain unaffected by pollution if they could switch away from bonds to other sources of capital, e.g., banks (Bergstresser and Orr, 2014), while keeping costs in check. However, bank loans account for just 5–10% of the debt for larger local governments and 10–20% for less populous municipalities, and such loans may also limit the ability of municipalities to issue public debts in future because bank loans almost always have shorter maturity and higher priority, and thus dilute the claims of bond holders (Ivanov and Zimmermann, 2019).

V. Differences from shocks such as hurricanes and the opioid crisis

Be it pollution, hurricanes or the opioid crisis, the overarching message is the same, municipal bond yields rise as a result. However, this conclusion hides important differences. Unlike pollution, these other shocks tend to affect municipalities of *all* types; additionally, in the case of hurricanes, intergovernmental transfers rise (Jerch et al., 2020), and in the case of the opioid crisis, municipal bond issuance declines (Cornaggia et al., 2021). On the other hand, drinking water pollution affects only general-purpose municipalities, does not result in higher intergovernmental transfers, and does not lead to a reduced tendency to issue bonds. President Dwight Eisenhower once said, water pollution is a “uniquely local blight”, and this paper finds that the financial burden of water pollution falls on local municipalities.

6 Conclusion

This paper examines the causal link between pollution and municipal finance using the unexpected discovery of PFAS contamination in 2016. Using this event in a difference-in-differences setting comparing the municipalities in contaminated counties with those from bordering, uncontaminated, same-state counties, the paper finds that pollution makes new municipal borrowings expensive in a manner consistent with increased municipal risk. Pollution also leads to a decline in public sector employment and municipal expenditure, thus adversely affecting the local economy.

Interestingly, the burden of pollution falls only on general-purpose municipalities, but not on special-purpose municipalities, because the former depend heavily on the local economy, while the latter enjoy wide-ranging federal and state support. Even general obligation bonds, which account for the largest share of municipal borrowing, experience a significant increase in yields. It is also surprising that, while municipalities are generally considered safe borrowers, their borrowing costs in the bond markets are highly susceptible to local pollution shocks.

It may also be useful to highlight that pollutants such as PFAS, which belong to a broader class of chemicals known as emerging pollutants, pose unique challenges to the economy. Unlike conventional pollutants, which are regulated and monitored for, the absence of regulations surrounding emerging pollutants may lead to not only widespread unchecked contamination, but also huge uncertainties in its remediation. Even simple questions such as who is responsible for and what technologies to use to test, monitor, and treat the contamination, who should bear the cost of cleanup, and who should invest in preventive infrastructure, have no clear answers.

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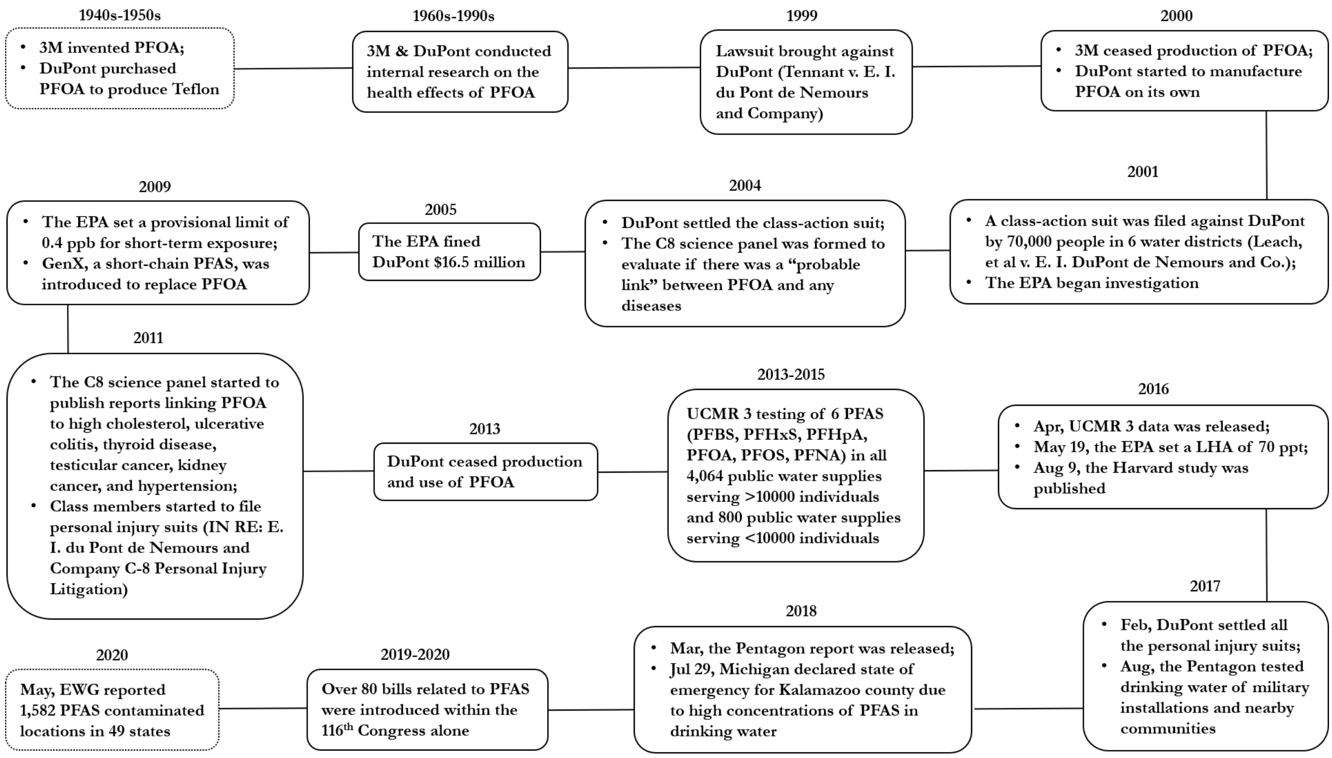
Figure I: Important Events surrounding PFAS

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



Information adapted from Rich (2016, Jan. 6), Soechtig and Seifert (2018), and the 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 contiguous U.S. the counties that were revealed under UCMR (3) to have PFAS in drinking water (*treated counties*) and the bordering but unpolluted same-state counties (*control counties*).

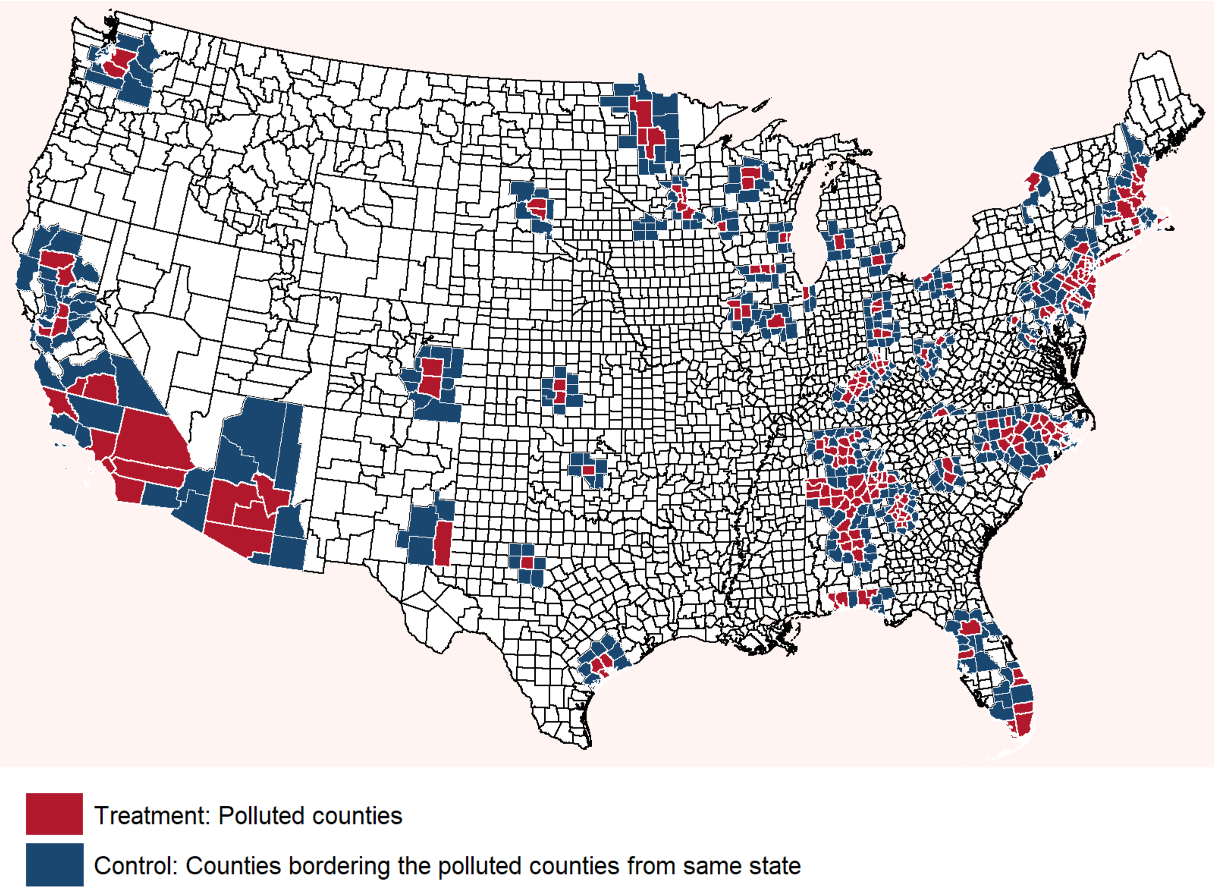
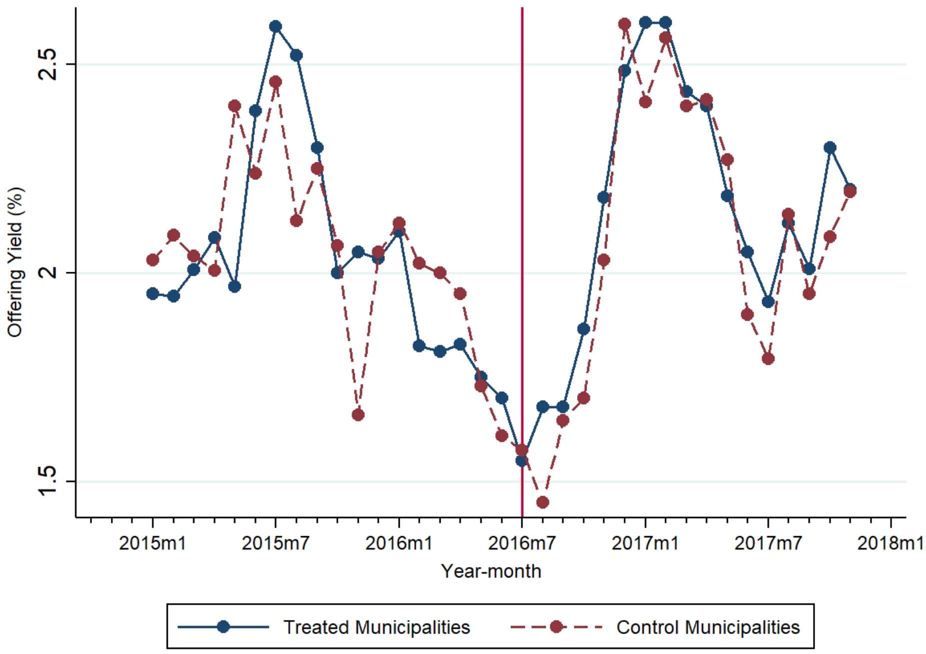


Figure III: Parallel Trends

This figure plots the offering yields of 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: Median Offering Yields



Panel B: Mean Offering Yields

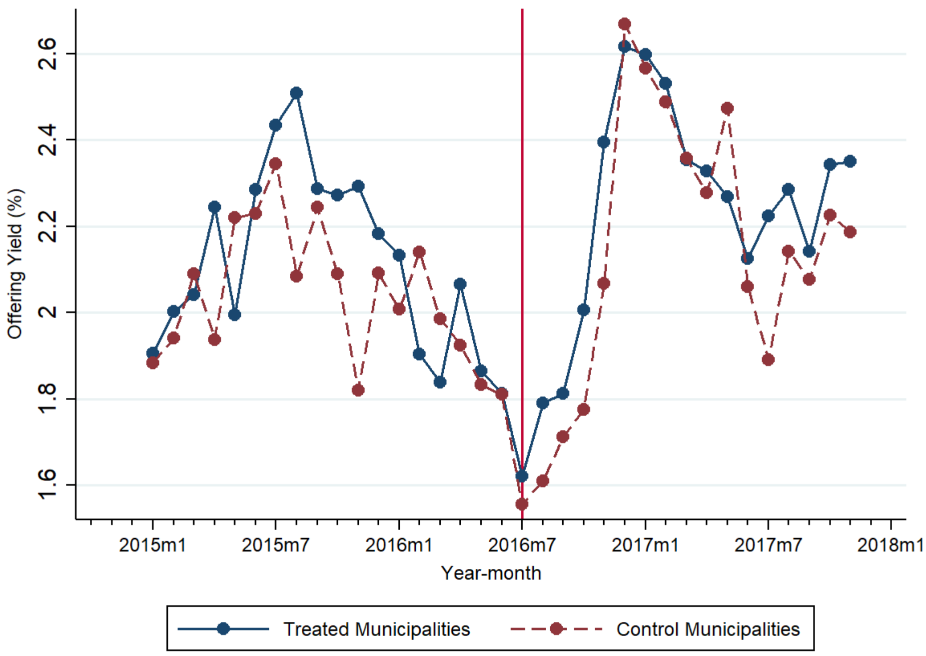
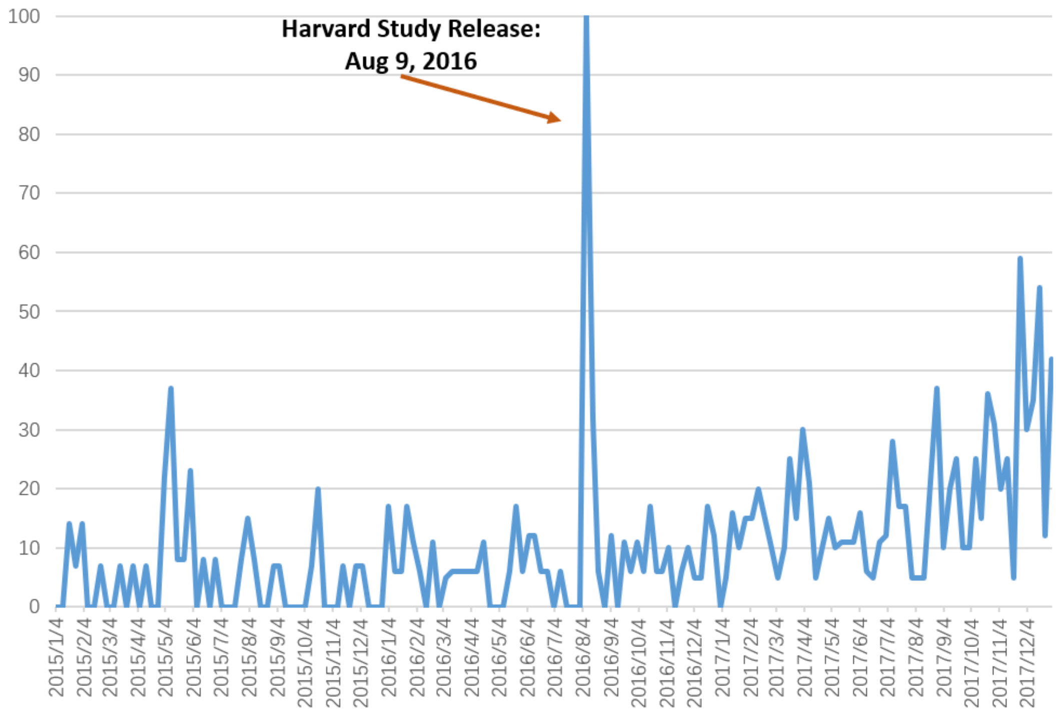


Figure IV: The Event

This figure illustrates the event. Panel (A) shows the publication of the findings of Hu et al. (2016) in the Harvard Gazette (The Harvard Gazette, Aug 9, 2016). Panel (B) plots the Google Search Interest for the term "PFAS" in the U.S. from 2015 to 2017. Panel (C) plots the average Google Search Interest for the keyword "PFAS" coming from the contaminated states and non-contaminated others. The contaminated states refer to the 33 states mentioned in Hu et al. (2016). The averages were calculated every half-year for the two sets of states using the Google Trends data 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 marks the timing of the event.

Panel A: The Harvard Gazette Article

Panel B: Google Search Interest for PFAS



Panel C: Average Search Interest for "PFAS" in Contaminated and Uncontaminated States

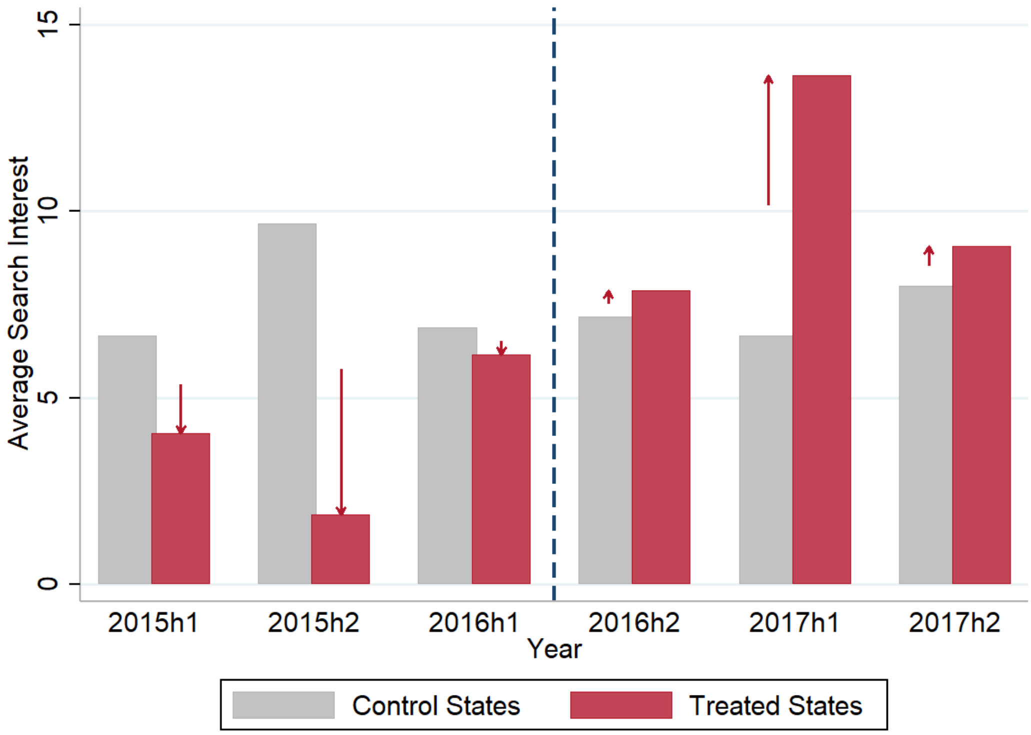


Figure V: Increase in Municipal Bond Yields due to Various Factors

This figure shows the effects on municipal bond yields of selected well-known factors reported by other studies. The vertical axis shows the magnitude of the estimated effect (in basis points) caused by the factor noted on the x-axis. 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). Yields (or yield spreads) are measured differently in some cases.

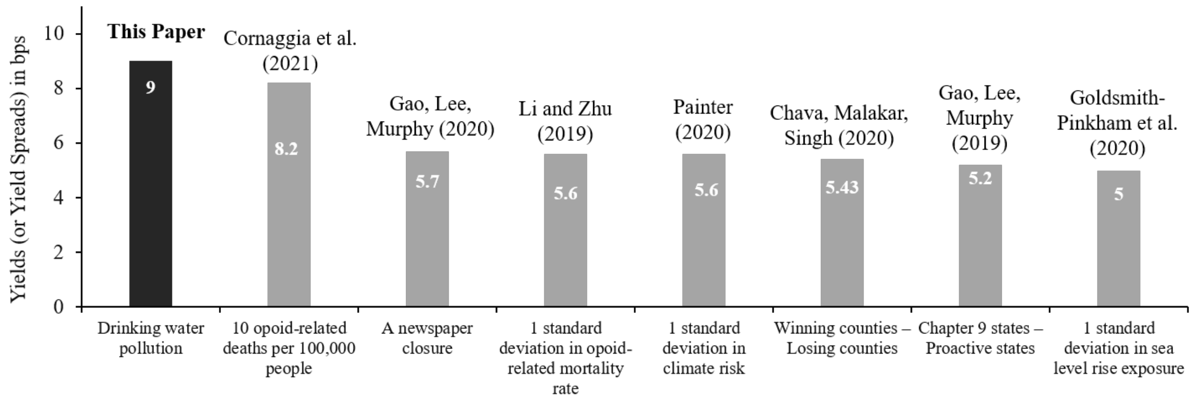


Figure VI: Location of Part 139-certified U.S. Airports by the ARFF Index

This figure shows the locations of 420 Part 139-certified airports on the map of contiguous U.S. according to their Aircraft Rescue and Fire Fighting (ARFF) index. The certification data are from March 29, 2016.

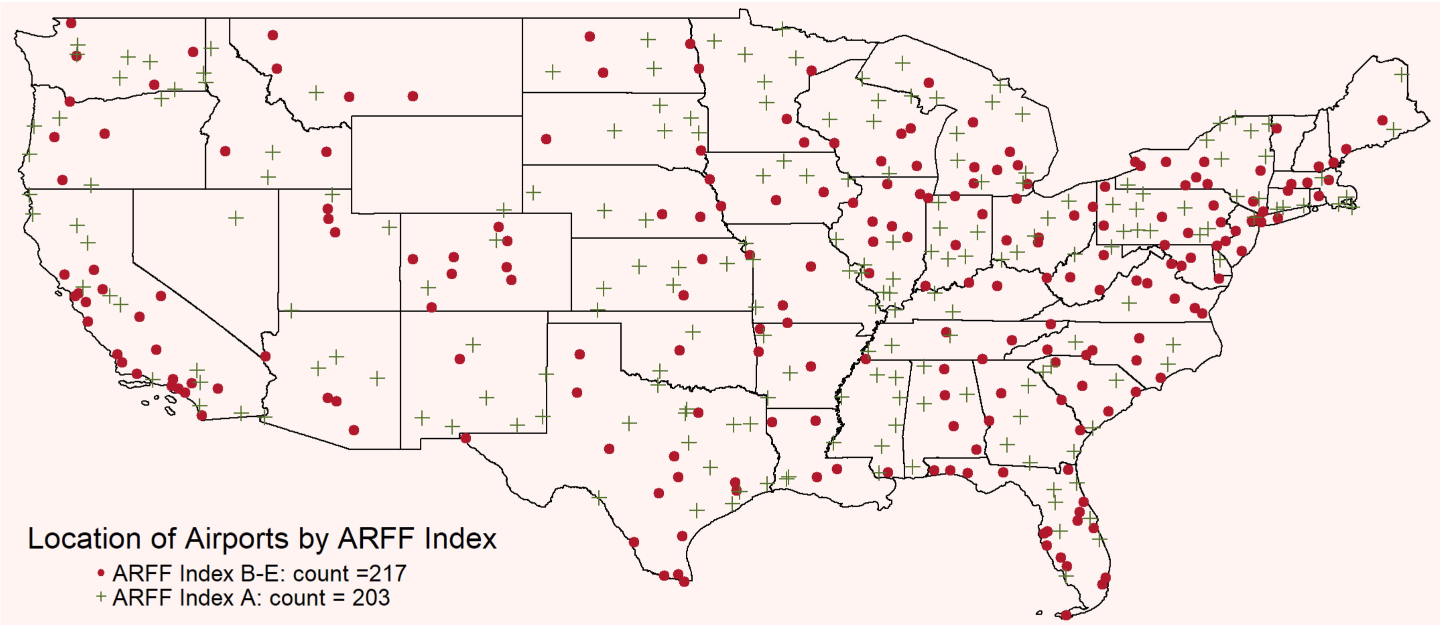


Table I: Summary Statistics

Panel (A) of this table shows the number and percentage of detected polluted counties and concentration-level summary statistics in our regression sample. *N* indicates the number of counties that detected any of the six PFAS, i.e., PFOA, PFOS, PFHpA, PFHxS, PFNA, or PFBS. In total, 123 unique counties detected at least one of the six PFAS chemicals. One county may become contaminated with more than one PFAS. MRL is the UCMR (3) minimum reporting level. Concentrations and MRL are in ng/L.

Panel A: Summary Statistics for Contamination-related Variables

	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 summary statistics for the key variables for the treatment group, control group, and both combined. *Off. Yld.* denotes offering yield, which is the yield to maturity at issuance (in percentages). *Coupon* is in percentages. *Issue Amt.* is the dollar amount issued in millions. *Tenure* is maturity of the bond measured at issuance (in months). *Issue Rating* is S&P's rating converted to a numerical scale that has the value 21 for a AAA rating, 2 for a D, and 1 for an unrated bond. *Tax Exempt* is a dummy variable taking the value of 1 if the bond is federal tax exempt and 0 otherwise. *Insured* is a dummy variable taking the value of 1 if the bond is insured and 0 otherwise. *Yld. Sprd.* denotes monthly yield spread (in percentage points). *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 dollar 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, respectively.

Panel B: Summary Statistics for Key Variables

	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 Per Capita	879	728.22	1122.07	542.79	545	739.79	1372.42	512.87	334	709.36	491.99	609.13
Intergov't. Rev. Per Capita	879	746.36	883.93	530.18	545	713.78	1016.80	470.35	334	799.53	605.40	674.70

Table II: PFAS Contamination and Offering Yields

This table reports the estimated treatment effects of pollution on offering yields of bonds issued by all municipalities (in Columns 1 and 2), general-purpose municipalities (in Columns 3 and 4), and special-purpose municipalities (in Columns 5 and 6). 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):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and $County\ Controls_{cst}$ 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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State×Year*" fixed effects. Standard errors are clustered 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**	0.06***	0.09***	0.09***	0.03	0.02
	(2.24)	(3.05)	(2.82)	(3.76)	(0.63)	(0.79)
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	72862	72068	45998	45649	26863	26418

Table III: Treatment Effects on Offering Yields by Repayment Obligation

This table reports the estimated treatment effects of pollution on offering yields of water revenue bonds (in Columns 1 and 2), general obligation (GO) bonds (in Columns 3 and 4), and other revenue bonds (in Columns 5 and 6). The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and $County\ Controls_{cst}$ 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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State*×*Year*" fixed effects. Standard errors are clustered 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***	0.05	0.10***	0.08***	-0.08	0.11
	(4.04)	(0.35)	(2.91)	(3.24)	(-0.80)	(1.41)
Bond & County Controls	×	✓	×	✓	×	✓
Issuer FE	✓	✓	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓	✓	✓
R^2 (Adj)	0.22	0.88	0.25	0.87	0.24	0.85
Observations	2292	2204	39343	39116	4324	4290

Table IV: Treatment Effects on Offering Yields by Bond Maturity

This table reports the estimated treatment effects of pollution on offering yields of municipal bonds of maturities >15 years in Columns (1)and (2) and of maturities ≤ 15 years in Columns (3) and (4). The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. *Treatment*$_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *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 federal tax exempt, and whether the bond is insured; and *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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State*$\times$*Year*" fixed effects. Standard errors are clustered 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***	0.09***
	(3.32)	(3.34)	(2.70)	(3.57)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.64	0.76	0.23	0.88
Observations	8147	7995	37797	37601

Table V: Treatment Effects on Offering Yields by *Ex-ante* County Debt Burden

This table reports the estimated treatment effects of pollution on offering yields of bonds issued by the municipalities from high debt-burden counties (Columns 1 and 2) and low debt-burden counties (Columns 3 and 4). To calculate the debt burden of a county, we aggregate the debt (total debt outstanding) of all the sub-state municipalities—county, municipal, and township governments—in the county and divide it by their aggregated total revenues. A county is then considered as having low debt burden if its ratio in the pre-event year (2015) was less than the cross-sectional sample average across counties and as having high debt burden otherwise. The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and *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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State*×*Year*" fixed effects. Standard errors are clustered 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**	0.08**
	(1.84)	(3.03)	(2.54)	(2.17)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.24	0.85	0.25	0.88
Observations	20344	20284	25007	24970

Table VI: Treatment Effects on Offering Yields by Tendency to Issue Unrated Bonds

This table reports the estimated treatment effects of pollution on offering yields of bonds issued by the municipalities whose tendency to issue unrated bonds is high (in Columns 1 and 2) and low (in Columns 3 and 4). The tendency is measured by the ratio of the unrated bond issuance amount to the total issuance amount annually. A municipality is then assigned to the high-tendency group if its ratio in the pre-event year (2015) was greater than or equal to the cross-sectional sample average of the ratio, and to the low-tendency group otherwise. The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and $County\ Controls_{cst}$ 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 Panel (B) of Table (I). All regressions include municipality fixed effects and "$State \times Year$" fixed effects. Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	High Tendency		Low Tendency	
	(1)	(2)	(3)	(4)
Treat × Post	0.20***	0.12***	0.02	0.06**
	(3.46)	(3.07)	(0.62)	(2.22)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.28	0.88	0.21	0.86
Observations	17108	16986	24573	24376

Table VII: Treatment Effects on Offering Yields by Chapter 9 Bankruptcy Provision

This table reports the estimated treatment effects of pollution on offering yields of bonds issued by municipalities from the states that have Chapter 9 bankruptcy provision (in Columns 1 and 2) and those that do not (in Columns 3 and 4). The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and *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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State*$\times$*Year*" fixed effects. Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Bankruptcy Provision		No Bankruptcy Provision	
	(1)	(2)	(3)	(4)
Treat $\times$ Post	0.11*	0.13***	0.09*	0.08*
	(1.97)	(3.51)	(1.87)	(1.98)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State $\times$ 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 municipal expenditure for different municipality types. *General-purpose* municipalities refer to municipal (2) and township (3) governments, and *special-purpose* to district (4) and school district (5). The numbers in parentheses indicate the *government type codes* assigned by the Census Bureau. The regression specification follows Equation (3):

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

Here m denotes municipalities and t indexes year. $Post_t$ takes the value of 1 for $t > 2016$ and 0 otherwise. In the left panel, the expenditures and revenues are expressed as dollars per capita, and in the right panel, in millions of dollars. The definitions of these variables are provided in Table (A.1). All regressions include municipality fixed effects and year fixed effects. N and $R^2(Adj)$ show the number of observations and adjusted R-squared corresponding to respective regressions. Standard errors are clustered by municipality. 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 Municipal 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) of this table shows the estimated treatment effects of pollution on county public sector employment. The regression specification follows Equation (4):

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

Public Employment$_{cst}$ refers to full-time equivalent public sector employment in year t in county c of state s. *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*×*Year*" fixed effects. Standard errors are clustered 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 Sector Employment

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

Table IX: Treatment Effects on Offering Yields using an Instrumental Variable-like Approach

Panel (A) of this table reports the estimates from regressing contamination measures on airport types. Airports that have an aircraft rescue and fire fighting (ARFF) index of B–E are classified as *polluting*, and those with index A as *non-polluting*. The regression sample includes all the zip codes in the U.S. that are within 20 miles of airports. The regression specification is a spatial autoregressive model from Equation (5), estimated using a generalized spatial two-stage least squares estimator:

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

Here z denotes zip codes. *Polluting Airport*$_{z \leq 20}$ is a dummy variable equal to 1 if the airport within 20 miles of zip code z is of the polluting type, and 0 if non-polluting. $\mathbb{W}\times$ *PFAS Contamination*$_z$ is the spatially lagged dependent variable that accounts for pollution diffusion. The spatial weighting matrix $\mathbb{W}$ is based on queen contiguity. The outcome variable in Column (1) is an indicator for whether there was PFAS contamination in zip code z, in Column (2) is the maximum concentration detected among the six *PFAS*, and in Column (3) is the concentration of *PFOA*. The latter two dependent variables are measured in ng/L. 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

	PFAS Contamination	Max 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: Treatment Effects on Offering Yields using an Instrumental Variable-like Approach (continued)

Panel (B) of this table shows the results of regressing offering yields on the $Post_t$ dummy. The regressions are estimated separately for municipalities within a 20-mile radius of polluting airports (Columns 1 and 2) and non-polluting ones (Columns 3 and 4). The specification follows Equation (6):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Post_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. *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 federal tax exempt, and whether the bond is insured; and *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 Panel (B) of Table (I). All regressions include issuer fixed effects and "*State*×*Year*" fixed effects. Standard errors are clustered 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 within 20 Miles		Non-polluting Airport within 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: Treatment Effects on Offering Yields by Bond's Bank-qualified Status

This table reports the estimated treatment effects of pollution on offering yields for non-bank-qualified bonds (in Columns 1 and 2) and bank-qualified bonds (in Columns 3 and 4). The regression specification follows Equation (2):

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

The outcome variable is the offering yield (in percentages) of bond i issued on date t by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ 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 federal tax exempt, and whether the bond is insured; and $County\ Controls_{cst}$ 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 Panel (B) of Table (I). All regressions include municipality fixed effects and "*State*×*Year*" fixed effects. Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Non-Bank-Qualified		Bank-Qualified	
	(1)	(2)	(3)	(4)
Treat × Post	0.10***	0.11***	0.06	0.05
	(2.65)	(3.26)	(1.52)	(1.59)
Bond & County Controls	×	✓	×	✓
Issuer FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Cluster (County)	✓	✓	✓	✓
R^2 (Adj)	0.23	0.85	0.23	0.92
Observations	32737	32489	12699	12600

Table XI: Treatment Effect on Yield Spreads

This table reports the estimated treatment effects of pollution on municipal bond's trading yield spreads. The estimates are presented in Column (1) for all bonds; in Columns (2–4) for water revenue bonds, GO bonds, and other revenue bonds; and in Columns (5–6) for bonds of municipalities from counties with an *ex-ante* high- and low-debt burden. The regression specification follows Equation (7):

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

The outcome variable is the yield spread (in percentage points) in month t of bond i issued by municipality m in county c of state s. $Treatment_{cs}$ equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. $Post_t$ takes the value of 1 for $t \geq$ August, 2016 and 0 for the earlier periods. $Bond\ Controls_{imcst}$ 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 the bond's dollar transaction prices; $County\ Controls_{cst}$ 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 CUSIP fixed effects and "*State×Year*" fixed effects. 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 allow us to link the municipalities with their location information come from SDC Global Public Finance database. These include 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 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 who have a non-U.S. location.

We link the above two datasets using county FIPS, and then use county adjacency information from the Census Bureau to identify the counties that border the contaminated counties and are from the same state. We focus only on those municipalities that issued bonds at least once before and after the event.

Finally, we collect the airport ARFF index data from the FAA as of March 29, 2016 (close to the event) and link it with PFAS contamination data using zip codes.

Table A.1: Government Finance Variable Definitions

This table presents the definition of variables related to local government finance, taken from Pierson et al. (2015). These definitions follow the classification scheme from U.S. Census Bureau's "Government Finance and Employment Classification" manual. Under the scheme, for debt-related variables, the alpha-numerals show the debt classification codes; and for other variables, the alphabet denotes the object codes representing the character categories and the number, the function 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)