A Toxic Inheritance: Municipal Consequences of PFAS Contamination Discovery*

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Abstract

Unaddressed environmental contamination in the past can have present adverse consequences. We examine the discovery of contamination of drinking-water systems of U.S. counties by discontinued per- and poly-fluoroalkyl substances (PFAS). Using a difference-in-differences approach, we find that municipal bonds from PFAS-contaminated counties experienced a 7 bps increase in yields compared to bordering, uncontaminated counties in the same state. This increase was more pronounced for non-general obligation, lower-rated, and shorter-maturity bonds, and for bankruptcy-allowed municipalities. Additionally, contaminated counties experienced increased out-migration and decreased municipal expenditure and public employment. Another approach utilizing airports as potential PFAS sources suggests the effect on yields was pervasive.

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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.

It is well understood that pollution has negative effects on human health, productivity, and economic outcomes. However, does the discovery of environmental contamination from the past, which remained undisclosed for decades, adversely affect the economic outcomes for the community which uncovers it? From the health and productivity perspective, the discovery itself would not have any economic consequences, because it is the contamination, rather than the discovery, that affects these factors. The discovery, however, does require investment in remediation technologies which may impose unforeseen financial burden on the affected community leading to adverse outcomes. In this paper we document such an effect in a causal manner in the context of the discovery of contamination of drinking water supply systems in the U.S. with the potentially fatal per- and poly-fluoroalkyl substances (PFAS).

The Environmental Protection Agency (EPA) tested for the first time the drinking water supply systems across the U.S. for the PFAS under the third Unregulated Contaminant Monitoring Rule (UCMR 3) program. In August 2016, it revealed that 200 counties across 33 states had their water supply systems contaminated with the PFAS. These substances had not been regulated or monitored prior to this, and there were no established legal limits for their concentration in drinking water. Using a difference-in-differences (DD) approach, we observed that the municipal issuers from the contaminated counties saw the offering yields on their bonds increasing by 6 basis points compared to the issuers from the bordering, uncontaminated counties from the same state. The results are robust to an expansive set of controls for bond and issuer characteristics and local economic conditions. The contaminated counties also suffered adverse economic consequences, evident in rising out-migration and declining municipal expenditure and public sector employment.

In order for our estimates to have a causal interpretation, an ideal event is the one that randomly exposes the counties to the contamination. We do not argue that the event in our DD approach—the discovery of PFAS contamination of the drinking water supply system—perfectly achieves that. These chemicals have been used for over more than five decades in a multitude of consumer and industrial products, hence it could leak into the drinking water systems for a wide variety of reasons, including inadequate pollution abatement infrastructure or more intense PFAS usage. In fact, understanding how PFAS leaches into the environment is still an evolving area of scientific research (Abunada, Alazaiza, and Bashir, 2020; Ahrens and Bundschuh, 2014).

However, we argue that four institutional features of our event suggest that the information revelation of contamination was close-to-exogenous to the *contemporary* economic conditions of the affected counties. First, the actual contamination could have happened anytime over the past five decades, making it unlikely that the estimated changes in the outcomes after the event are correlated with the unobserved factors that caused the actual contamination deep in the past. Second, we use the uncontaminated counties bordering the contaminated counties from the *same* state as the counterfactual control. These counties are subject to the same state-level fiscal policies and are likely to experience broadly similar economic conditions. Third, predicting which counties were contaminated before the event was highly infeasible because the detection technologies available then had a limited sensitivity (EPA, Jan 2017) and special precautions are required to avoid cross-contamination when sampling and analyzing PFAS (Dorrance, Kellogg, and Love, 2017). Finally, potential incentives of legal liability claims against entities responsible for contamination did not exist, because there were no enforceable safe-limits on PFAS then and scientifically identifying the contamination source is highly uncertain, as described earlier.[1] EPA issued the first non-enforceable limits on PFAS on May 16, 2016, just a few months before the event.

Our empirical approach derives the causal estimates by relying on the release of information in the future about the contamination that occurred in the past. This strategy is similar to the approach used in Gormley and Matsa (2011) and Lam (2019). Their

[1] The high costs of the PFAS detection technology further reduces the potential gains from privately obtaining the contamination information. The sample collection and testing alone under UCMR (3) cost the EPA about $87 million (U.S. Government Accountability Office, 2014).

idea is that the revelation of the information that certain chemicals are harmful is an event that randomly exposes the firms already using those chemicals.[2] Also, since our estimates are based on the DD approach, alternative explanations based on macroeconomic events such as the surprise election of Donald Trump as President in 2016 raising the municipal bond yields across the board cannot explain the differential increase in the offering yields for municipalities from bordering counties within the same state.

Beyond quantifying the effects of PFAS contamination discovery on municipal bonds, the economic impacts of this event are of broader general interest. It is important to acknowledge that the PFAS contamination is not an isolated event. The legal and regulatory landscape surrounding these chemicals is rapidly evolving, with the implementation or consideration of ultra-low detection limits at both federal and state levels (Dorrance et al., 2017). Moreover, given the widespread usage of these chemicals in the past, areas that would require PFAS cleanup are expected to increase in the U.S. In fact, following the initial discovery in 2016 of PFAS contamination under UCMR 3, a total of 1,938 contamination sites have been discovered spanning all 50 U.S. states (The PFAS Project Lab, n.d.). Understanding the economic effects of such episodes is also important because a similar pattern of contamination may emerge in other countries. Besides, economic costs the communities in the future may have to incur due to the contamination in the past also illustrates that such contamination should be dealt with sustainably and carefully in the present.

We begin our analysis with understanding the salience of the event. The contamination revelation was a sudden shock and received widespread publicity (The Harvard Gazette, Aug 9, 2016; Hu et al., 2016). Google searches for the keyword "PFAS" surged, and relatively more searches came from contaminated areas.

Our baseline estimates comparing primary market offering yields on municipal bonds suggest that the issuers from the polluted counties suffered an average increase

[2] Studies in the household finance literature also use similar strategy, whereby contemporary changes in the interest rates are taken as exogenous shocks to the contemporary monthly payments of the households, but the assignment of these households to the treatment group occurs based on their past decision to take an adjustable rate mortgage (instead of a fixed rate mortgage) (Di Maggio et al., 2017; Gupta, 2019; Fuster and Willen, 2017).

of 5–7 basis points (bps) in offering yields vis-à-vis the issuers from the bordering uncontaminated counties from the same state. These estimates are robust to the inclusion of a host of controls for the bond characteristics and county-level economic conditions, bond rating fixed effects, highly granular municipality fixed effects, and $state \times year$ fixed effects. Moreover, unlike the trading yields (measured using the trade prices in the secondary market), the offering yields are primary market yields. An increase in the offering yield results in higher interest payments for the issuing municipalities. In terms of magnitude, a 6-bps increase in offering yield is equivalent to a $671-million increase in the interest expenses in present value terms or a 9.5-bps increase in the annual property taxes.

We hypothesize that the unexpected increase in operational budget of the affected municipalities due to the contamination discovery increases their default risk, raising the offering yields on new borrowing. The default risk likely increases, because (i) municipal issuers are expected to balance their operating budgets; and (ii) they are restricted by statutes, charters, and state policies to borrow for the long term to finance only infrastructure investments and such borrowings are subject to voter approval (Ang, Green, Longstaff, and Xing, 2017; Haughwout, Hyman, and Shachar, 2021).

We find evidence in support of the default risk hypothesis in a series of cross-sectional tests based on several bond and issuer characteristics and state policies that the municipal literature commonly associates with risk (K. R. Cornaggia, Hund, Nguyen, and Ye, 2021; K. Cornaggia, Li, and Ye, 2021, 2022; Gao, Lee, and Murphy, 2020). We specifically analyze the sub-samples of (i) general obligation (GO) bonds and others; (ii) bonds with high and low rating; (iii) bonds from states that allow municipalities to access the Chapter 9 Bankruptcy Code (Frost, 2014) and those who proactively assist municipalities (Gao, Lee, and Murphy, 2019); and (iv) bonds with long and short maturity. The increase in yield was more for non GO bonds, low-rated bonds, and for issuers from states allowing municipalities to declare bankruptcy. Since these characteristics have been shown to capture a dimension of municipal risk, it can be concluded that the yields increased more for riskier bonds. In terms of cross-sectional test based on bond maturity, the estimates allow us to distinguish whether it is the increased financing needs causing the yields to rise or is it certain characteristics of affected municipalities that get revealed by the contamination discovery and subsequently get priced into offering yields. The financing-needs hypothesis would predict an increase in offering yields of bonds of shorter maturity, because the increased financing needs would likely create more imbalances in the operational budget in the short run than in the long run. The revealed-characteristics hypothesis would predict an increase in the offering yields of all bonds regardless of the maturities, because municipality specific characteristics would be priced in all bonds. We find that the shorter-maturity bonds (less than ten years) experienced larger increase in offering yields than the longer-maturity bonds, corroborating the financing-needs hypothesis.

We identify two factors contributing to the increase in default risk of the affected municipalities: fiscal distress, similar to findings in Cheng, De Franco, and Lin (2023); Hastie (1972); Gao, Lee, and Murphy (2022); Hasan, Krause, and Qi (2020); Chava, Malakar, and Singh (2023), and migration induced shrinkage in economic base, similar to findings in (Hastie, 1972; J. Cornaggia, Gustafson, Israelsen, and Ye, 2019). We measured fiscal distress as the ratio of county-aggregated net revenues to total interest payment and found that counties having higher pre-event fiscal distress experienced more increase in yields after the event than those with lower pre-event distress. For shrinking economic base, we found that the affected counties experienced higher out-migration within state than that by surrounding control counties. Also we do not find evidence of declining home prices.

Our hypothesis regarding operation imbalances in municipal budgets predicts that municipalities would take up activities that reduce cash outflows. We thus examine the treatment effect on municipal expenditure and public employment. County-aggregated per capita municipal expenditure declined by USD 155 in affected counties relative to the control, a reduction of about 4% from the expenditure in the pre-event period. Moreover, per 1000 public employment reduced by 2.65 in the contaminated counties, equivalent to a decline of about 11% from the levels in pre-event period in affected counties. All in all, these findings are consistent with the operational budget hypothesis. They also show that the adverse real effects of contamination discovery include reduced spending on public services and public employment, in line with (Chava et al., 2023).

A limitation of our empirical strategy is that in order to lend causal interpretation to our estimates, we rely on municipalities from just a few counties, 200 contaminated and 426 uncontaminated. To measure whether the effect was widely pervasive, while retaining the causal interpretation, we employ an instrumental variable (IV) strategy. Environmental research has found that airports are one source of PFAS contamination, because they use it for fire suppression. In fact, most airports in the U.S. are federally mandated to use PFAS for fire extinguishing (Part 139 Certification of Airports, 2004). First, using the PFAS contamination locations we confirm that the zip codes within 40 miles radius of an airport were more likely to be detected with PFAS contamination than the zip codes located in a donut radius of 40–50 miles from the same airport (outside the 40-mile circle). The inference is robust to varying the donut radius to 60, 70 or 80 miles. The exclusion restriction here is that airports do not affect the municipal yields of municipalities located within 40-mile circle and those located just outside the circle differently other than its effect through PFAS contamination.

The airport IV allows us to test the contamination effect on the bond yields of municipalities across the U.S., not just those located in the contaminated counties discovered by EPA. We employ the circle-donut empirical design comparing the municipalities within 40-mile circle of an airport to those located outside the circle in a donut of different radii. We consistently find that offering yields of the municipalities close to airports increased by almost 13–14 bps relative to those located in the donut area. These estimates are robust to the inclusion of the same set of exhaustive controls as we used in the main sample. The findings suggest that increase in offering municipal yields was pervasive.

Finally, to capture investors' expectation of the effect of PFAS contamination on the bonds issued by the affected municipalities, we also examine the changes in the trading yields in the secondary market. Consistent with the primary market rising yields on bonds of municipalities from the contaminated counties, the trading yields in the secondary market too experienced an increase of 7–9 bps.

Overall, we show that discovering contamination that occurred in the deep past affects the community that uncovers it in the future through the municipal finance channel. The economic impacts of such discovery include increased out-migration and unfavorable changes in public employment and municipal expenditure. The findings also highlight a potential cost future communities may need to incur, if contamination is not addressed proactively in the present. Understanding these adverse effects is also important because municipalities play a crucial role in local economic development. 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 (Agrawal and Kim, 2021; 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).

This paper primarily contributes to the growing literature on municipal finance, showing that municipalities are affected by the discovery of unaddressed contamination from the past. Several other factors have been shown to affect municipal bonds, such as green certification (Baker, Bergstresser, Serafeim, and Wurgler, 2018), climate change (Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2023; Painter, 2020), environmental regulations (Jha, Karolyi, and Muller, 2020), hurricanes (Jerch, Kahn, and Lin, 2020), the opioid crisis (K. R. Cornaggia et al., 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 et al., 2020), and state pension under-funding (Boyer, 2020; Novy-Marx and Rauh, 2012).

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 Table (I) the key events related to PFAS.[3]

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).[4] Relying on the data from the pro-

[3] 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.

[4] 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

gram, 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 (III). 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-randomly, 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 III, Panel B), and relatively more searches came from the contaminated vis-à-vis non-contaminated states (Figure III, Panel C). Even though these measures of search reflect views of overall population and not the municipal investors, still since retail participation accounts for about half of all municipal holdings, the differential increase in searches do suggest that the event gained widespread attention.[5]

Consequences for the Municipalities

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

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.

[5] 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.

eas in Pennsylvania was stalled after the contamination was discovered (The Philadelphia Inquirer, 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.[6] Second, local enforceable limits on PFAS were legislated.[7] More than 80 pieces of legislation were introduced in the 116$^{\text{th}}$ Congress (National Conference of State Legislatures, Jan 25, 2021), and a federal regulation concerning 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 same state but did not have PFAS contamination; August 9, 2016, serves as the event date. The sample consists of 200 treated counties and 426 control counties from across 33 states, as shown on the map of the contiguous U.S. in Figure (I).[8] 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

[6] 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)

[7] 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.).

[8] 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.

a variation of the empirical strategy used in Dube, Lester, and Reich (2010), among others.

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

$$\text{Outcome}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \delta \text{ Controls}_{imcst} + \text{Rating}_i + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst} \; , \tag{1}$$

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.

$Rating_i$ represents bond rating fixed effects. These account for differences in outcome variable for bonds of different ratings. 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.

Parallel Trends Assumption

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 DD 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, the coefficients obtained from the following regression shed some light on it:

$$\begin{aligned} \text{YTM}_{imcst} = \alpha_0 + \sum\nolimits_{k=T-3}^{T-2} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum\nolimits_{k=T}^{T+2} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k \\ + \delta_1 \text{ Bond Controls}_{imcst} + \delta_2 \text{ County Controls}_{cst} + \text{Rating}_i + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst} \end{aligned} \tag{2}$$

where T = Event year 2016. $\quad$ $\text{Year}_k = 1$ if $t = T - k$. $\quad$ $\text{Year}_k = 0$ if $t \neq T - k$, k={-3,3}.

The plot of the coefficients on β's in Panel A of Figure (II) reveals that the offering yields were not statistically different for the municipalities from the contaminated and bordering uncontaminated counties prior to the event, but the difference emerges after the event. This provides some assurance that the yields would have followed a parallel trend in the absence of the event.

Moreover, we examine the trend in county-level economic variables using the following regression equation:

$$\begin{aligned} \text{Outcome}_{cst} = \alpha_0 + \sum\nolimits_{k=T-3}^{T-2} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum\nolimits_{k=T}^{T+2} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k + \\ \alpha_c + \gamma_{sy} + \varepsilon_{cst} \end{aligned} \tag{3}$$

Panel (B) through (D) of Figure (II) plots the β's for the three variables—growth rate of income per capita, employment, and property taxes per capita. We see that the treated and control counties did not experience a significantly different trend in terms of these economic indicators. Overall, these analyses support the parallel trends assumption.

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 finance data from the Annual Survey/Census of State and Local Government Finances, compiled by Pierson, Hand, and Thompson (2015), public sector employment data from the Annual Survey of Public Employment & Payroll (ASPEP), and migration data from Inland Revenue Service Statistics of Income Division (IRS SOI). Furthermore, data from the Bureau of Economic Analysis (BEA) are used to capture local economic conditions, and data from the Federal Aviation Administration (FAA) on airport locations are used in an alternative identification strategy.

The municipal issuance data contain a host of information on new municipal bond issues such as yield, coupon, amount, etc., and the trade data specify information such as trading yield and amount of the transaction. 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, we create the *volume weighted monthly average of trading yields*. The regression sample for new bonds consists of 56,886 bonds (at the CUSIP level) issued by 1,738 municipalities in the treated group and 43,752 bonds issued by 1,370 municipalities in the control group. Similarly, the sample for already-issued bonds consists of 158,382 bonds issued by 3,944 municipalities in the treated group and 119,306 bonds by 3,335 municipalities in the control. 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., 2023; R. C. Green, Hollifield, and Schürhoff, 2007).

Panel (A) of Table (II) 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 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 200 counties that had PFAS contamination, 128 (64%) had PFOA, with a mean detection level of 48.5 ng/L and a maximum of 349 ng/L, almost five times the EPA's lifetime health advisory.

Columns (1) through (4) in Panel (B) of Table (II) 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 2.29%, coupon of 3.42%, maturity of 9.6 years, and Moody's rating between AA2 and AA3 (1 for an AAA rating, 2 for an AA1, and 26 for the lowest rating). On average, an issue raises 3.77 million dollars. In terms of secondary market transactions, a bond on average has a trading yield of 2.36% and trades 7.79 times per month. The monthly standard deviation of dollar prices is 0.69. With respect to economic conditions, an average county during the sample period experienced annual growth rates of 3% in per capita income, 5% in property taxes per capita, and 1% in the number of employment.

Columns (5) through (8) in Panel (B) of Table (II) shows statistics on the growth rates of each of these variables measured over the pre-event time period for treated and control counties. Column (8) shows p-values from the t-test for the difference in the growth rates of each of these variables experienced by the treated and control counties over the pre-event time period. All the p-values are statistically insignificant, supporting further the parallel trends assumption (as the plots in Figure II do).

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:

$$\begin{aligned} \text{Off. Yld.}_{imcst} = \alpha_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \text{Rating}_i + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst} \ , \end{aligned} \tag{4}$$

where *Off. Yld.* is the offering yield of bond i (at CUSIP level) issued by municipality m from county c of state s in year t. β_1 is the coefficient of interest. *Bond Controls*$_{imcst}$ include bond size (in millions), Moody's credit rating, tenure (in months), and indicators for whether the bond is federal tax exempt, callable, insured, and whether the offering type is competitive or negotiated. *County Controls*$_{cst}$ include annual growth rates of (personal) income per capita, property taxes per capita, and the number of employment per 1,000 population. *Rating*$_i$ denotes bond rating fixed effects, taking the value of 1 for an AAA rating, 2 for an AA1, $\cdots$ 26 for the lowest rating. α_{mcs} denotes municipality fixed effects and γ_{sy} denotes "*State*$\times$*Year*" fixed effects.

Table (III) shows the results of the above regression. The estimates of β_1 suggest that a new bond issued by a municipality in a polluted county experienced an increase of 5–7 bps in offering yields relative to a municipality from a neighboring uncontaminated county after the revelation of the contamination. 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*$\times$*Year*" fixed effects, and to a broad set of controls. The inclusion of rating fixed effects further partials out any differences in offering yields of bonds of different ratings. Our preferred estimate comes from the specification with both bond and county controls in Column (3). The rise in offering yields of the affected municipalities supports the conclusion that their borrowings were deemed riskier after the pollution was revealed.

To understand whether a 7-bps increase in the offering yield economically large, we note that it is equivalent to a 3.9% increase over the average yields of the affected general-purpose bonds paid in 2016 (before the event). In present value terms, it represents $783 million more in interest costs.[9] If financed through annual property taxes, the increased interest payments would be equivalent to raising the taxes by 11 bps ($80 million interest payment as a fraction of $71 billion property taxes in 2017). From the perspective of the relative strength of the effect, in Figure (**??**) we compare the effect of pollution with that of other well-known factors. From the figure, the increase in yields due to the PFAS contamination discovery appears to be economically as important as some of the other factors reported in the municipal literature.

We hypothesize that the increase in the expected operational expenses of the municipalities to provide for the remediation of PFAS contamination raises their default risk, causing the yields to rise. The default risk likely increases because almost all municipalities are required by statutes, charters, or state constitutions to balance their operating budgets and are allowed to borrow long term only for capital projects subject to approval by voters (Ang et al., 2017; Haughwout et al., 2021).

4.2 Effect Heterogeneity by Risk Characteristics

Thus to corroborate this hypothesis, we conduct a series of cross-sectional tests dividing the sample according to characteristics understood to be associated with risk in the municipal finance literature (K. R. Cornaggia et al., 2021; K. Cornaggia et al., 2022; Gao et al., 2020).

4.2.1 Repayment Obligation: General obligation bonds versus revenue bonds

Depending on the cash flows that back their repayments, municipal bonds are of two broad types: general obligation (G.O.) bonds and revenue bonds. G.O. bonds, which account for the bulk of public borrowing, are backed by the taxation power of the municipalities and hence carry lower default risk than a revenue bond. Thus the effect of the event should be less pronounced for G.O. bonds than for other bonds. We test this

[9] These municipalities from the polluted counties borrowed $114 billion in bonds with an average maturity of 121 months in 2017. The 7 bps, or $79.8 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 $782.9 million.

by first estimating Equation (4) separately for G.O. and non-G.O. bonds, and then estimating a triple difference model with a dummy for G.O. bonds. Table (IV) shows the results. We see that while offering yields increased for both set of bonds, the increase was 8 bps more for revenue bonds. This is consistent with the risk-based explanation for the increase in yields after contamination discovery.

4.2.2 Bond rating

Bond credit ratings are one of the most direct indicators of default risk of the issuing municipalities. While the ratings do reflect risk of default, they are too coarse to fully reflect differences in credit quality across all rated securities (J. Cornaggia, Cornaggia, and Israelsen, 2018; Goel and Thakor, 2015), and they are traditionally designed to be stable over time and not to reflect real-time changes in credit quality. All our previous regressions included bond's rating fixed effects, accounting for the effect of default risk on yields. However, to the extent that ratings do not fully capture default risk, the increase in yields should be higher for lower rated bonds. We test this by assigning the bonds having a Moody's rating of AA2 and above (numeric rating ≤ 3) to high rating category and those with a rating worse than AA2 (numeric rating > 3) to low rating category. Just as before, we estimate the treatment effect on offering yields separately for bonds in the two categories using Equation (4).

The results are shown in Panel (A) of Table (V). Consistent with the prediction, the treatment effect was higher at 8 bps (*p-val 0.104*) for bonds in low rating category compared to 6 bps for those in the high category. Using a triple-difference model, we also test whether the increase in yields for the bonds in the low category after the contamination discovery was more than that for the bonds in high category. The coefficient on $Treat \times Post\ HighRating$ in Column (3) suggests that on average the high rated bonds had 12 bps lower increase than low-rated bonds.[10] This corroborates the prediction the bonds with low rating suffered higher increase in yields than bonds with high rating.

[10] Note that the inclusion of bond rating fixed effect will absorb the indicator *High Rating* in the triple-difference specification, so it is unreported in Column (3).

Nonetheless, to the extent that contemporaneous bond ratings would have taken into account the effect of contamination discovery, the cross-sectional differences documented above would underestimate the true difference. Hence to estimate the true difference in the increase in yields of bonds of different rating categories, we create an *ex ante rating* for each municipal issuer as the average of the numerical bond rating of all the bonds it issued in the pre-event sample period (2013–2015), in the spirit of Gao et al. (2022, Footnote 5). We then use cross-sectional mean of this issuer-level rating to classify the issuers as high-rated if their *ex-ante rating* $\leq$ *cross-sectional mean* (because lower value reflects higher rating) and as low-rated otherwise.

The results of using this measure are shown in Panel (B). While the conclusions remain the same as the earlier analysis suggested, we see that estimates in each subsample and in the triple-difference specification is now 1 bps higher than found earlier using contemporary ratings.[11] Thus contemporaneous bond ratings do adjust, but not fully, to reflect the effect of contamination discovery on default risk.

4.2.3 Bond maturity

All our previous results controlled for bond's maturity, so they mask the heterogeneity for bonds of different maturities. We now examine the effect heterogeneity across bond maturity to distinguish between the two hypotheses: (i) is the increased financing needs of municipalities to remediate the discovered contamination the reason for increased offering yields; or (ii) does the contamination discovery reveal certain municipal characteristics indicative of operational inefficiencies? The financing-needs hypothesis would predict that the yields would rise for bond borrowings in the short run, because the remediation needs cannot be postponed indefinitely. On the other hand, the revealed-characteristics hypothesis would predict that offering yields would rise across the investing (time) horizon, because the revealed characteristics would get priced into all bonds issued by the affected municipalities (not only priced into their

[11] Note that the inclusion of bond rating fixed effect absorbs the indicator *High Rating* in the triple-difference specification. Similarly, since the rating classification variable is defined at the issuer level, the inclusion of issuer fixed effect absorbs *Treat* $\times$ *High Rating* in the triple-difference specification. So these coefficients are unreported in Column (3).

bonds of shorter maturity). Chordia, Jeung, and Pati (2022); Painter (2020) also use examine effect heterogeneity by bond maturity to distinguish alternative hypotheses.

To examine how do offering yields in affected counties relative to the control change by maturity of the bonds, we classify the bonds into two groups: maturity <10 years and ≥ 10 years. We use Equation (4) to estimate within group change in the offering yields first. The estimates in Columns (1) and (2) of Table (VI) for within-maturity changes suggest that offering yields increased by roughly the same amount for both long and short maturity bonds compared to the control. However the triple-difference estimate in Column (3) reveals that the longer-maturity bonds experienced a 8 bps lower increase in offering yields than the shorter-maturity bonds. These findings are in line with the financing-needs hypothesis and contradict revealed-characteristics hypothesis.

4.2.4 Municipal bankruptcy and state assistance policy

Policies to assist municipalities vary significantly across states and allow us to check for the default risk channel. The federal Chapter 9 of the U.S. Bankruptcy Code allows municipalities to file for bankruptcy. Specifically, 26 states have some form of policy in place to allow distressed municipalities to file for Chapter 9 bankruptcy. 15 states allow blanket authorization (AL, AZ, AR, CO, FL, ID, KY, MN, MO, MT, NE, OK, SC, TX, and WA) and 11 allow conditional access (CA, CT, LA, NC, OH, NV, NJ, NY, PA, MI, and IL) (Frost, 2014, footnote 81, 93, and 100). Furthermore, Gao et al. (2019) report that nine states proactively have policies to financially assist distressed municipalities (ME, MI, NC, NJ, NY, OH, PA, NV, and RI). They also show that risk of default is higher for municipalities in states allowing Chapter 9 bankruptcy, and so offering yields of bonds issued by them are higher too. Given our hypothesis that contamination discovery increases default risk of municipalities, the increase in offering yields should be larger for the municipalities from bankruptcy-allowing states compared to those from proactive states. We examine this prediction next.

We take the union of the 26 bankruptcy states and nine proactive states above and classify them into proactive and non-proactive groups. Just as before, we quantify within group estimates in a DD setting using Equation (4) and cross-group difference using a triple-difference specification. Table (VII) shows the result. Consistent with the risk explanation, with respect to the respective control municipalities, the affected municipalities in non-proactive Chapter 9 states saw a 9-bps increase in offering yields (Column 1). On the other hand, the affected municipalities in proactive states saw a non-significant increase of just 4 bps (Column 2). The triple difference specification in Column (3) shows that the offering yields of affected municipalities in proactive states rose on average 8 bps lower than in non-proactive bankruptcy states.

All in all, the differential increase in offering yields according to all the four risk proxies above corroborate that contamination discovery leads to increased municipal default risk.

4.3 Mechanism

We next examine the economic factors that underlie the increase in default risk of municipalities. The two factors we look at are fiscal distress and population migration.

4.3.1 Fiscal distress

To understand the role of fiscal distress in raising the offering yields, we follow an approach similar to the one used by Chava et al. (2023); Cheng et al. (2023); Gao et al. (2022) and Hasan et al. (2020). The idea is to classify the municipalities into high and low fiscal distress using their financial condition in the pre-event period and estimate the change in offering yields within and across the two groups. We measure fiscal distress as the county-aggregate interest coverage ratio.[12] The counties that had the ratio > cross-sectional median in the pre-event period is in low distress group, others in

[12] Specifically, using government finance data from (Pierson et al., 2015), we first calculate net revenue as *General Revenue from Own Sources − Total Expenditure* and then aggregate it across all municipalities to the county-year level (A). Then we aggregate *Total Interest on Debt* to the county-year level (B). We define county-year level interest coverage ratio as the ratio of A to B. We consider all municipal governments at county and smaller level (i.e., state and federal government are excluded). We use county-aggregate ratios because individual municipal entities in the bond data (Eikon and MSRB) do not correspond one-to-one to the municipal entities in the government finance data. The entities in the later data are identified as city, town, village, county etc., but not individual municipality. We aggregate these variables to the county-year level also to ameliorate the issue of missing data for smaller municipalities for the years not ending in 2 or 7 (Chordia et al., 2022; Pierson et al., 2015).

high distress group. We then examine the treatment effect within group using Equation (4) and across the groups using a triple-difference specification. Estimates in Table (VIII) show that relative to the control, the affected municipalities in counties with *ex-ante* high fiscal distress experienced a larger increase (10 bps, Column 1) than those in counties with *ex-ante* low distress (6 bps, Column 2). Finally, consistent with the fiscal distress channel, the triple-difference estimate in Column (3) show that low-fiscal distress municipalities saw a smaller increase of 9 bps (Column 3).

4.3.2 Shrinking economic base

A second factor that can increase municipal default risk is a shrinkage of economic base (Hastie, 1972; Yi, 2020; J. Cornaggia et al., 2019). Specifically we examine whether contamination discovery increases out-migration from affected counties, leading to a decrease in future taxable economic base. We utilize county-to-county migration data from IRS SOI data. We calculate "within state net out-migration" for a focal county as outflow to other counties within same state - inflow from other counties from the same state divided by the focal county population. We use the following regression equation for these outcomes:

$$\begin{aligned} Y_{cst} = \ & \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \text{ County Controls}_{cst} \\ & + \alpha_{cs} + \gamma_{sy} + \varepsilon_{cst} \ , \end{aligned} \tag{5}$$

where c refers to county, s to state, and t to year; α_{cs} is the county fixed effects; and standard errors are clustered by county. $Post_t$ takes the value of 1 for $t \geq 2016$ and 0 otherwise.

Columns (1) and (2) of Table (IX) suggest that relative to the control, the population outflow from the affected counties to other counties in the same state increased by about 0.11 percentage points after the discovery of PFAS contamination. This effect is large considering that the average out-migration flow in the treated counties in the pre-event period was -0.09% (net in-migration).

Overall we conclude that fiscal distress and migration contribute to the increase in default risk of municipalities after contamination discovery.

4.4 How Municipalities Responded?

Our hypothesis that the contamination discovery creates imbalances in the operational budget of affected municipalities raising their default risk also predicts that they would respond by reducing activities related to cash outflows. We thus examine the public (municipal) expenditure and public sector employment at the county level. We aggregate total public expenditure, which combines direct expenditure and intergovernmental expenditure, to the county-year level for all county and smaller municipal governments. Pierson et al. (2015) provide formal definition of the expenditure and underlying data. The regression specification is from Equation (5), and results are shown in Table (X).

Columns (1) and (2) indicate that relative to the control, the affected counties experienced a significant decline in total public expenditure of about 156 dollars per capita. This is equivalent to a 3.8% decline from the expenditure in affected counties in pre-event period. Moreover, we obtain similar estimates for the decline when using alternate measures of public expenditure, such as direct general expenditure.[13] Columns (3) and (4) show the estimates for public employment per 1000 population. It decreased by about 2.6 relative to the control counties, which is equivalent to a 11.6% decline from the average public employment in the affected counties in the pre-event period. In unreported estimates, we also find that the share of public sector employment in total employment dropped by about 0.8 percentage points (*p-val*$<$*0.001*). Overall, the effect of contamination discovery on the public sector employment is economically large and is also in line with the findings of Amornsiripanitch (2022) and Chordia et al. (2022).

Overall, municipalities responded to the increase in offering yields by reducing public expenditure and employment, likely due to anticipated imbalances in their operational budget. These declines also highlight the adverse real effects of contamination discovery. In unreported results, we find that house prices (measured by county-level

[13] It is the sum of current expenditures used to pay employees, purchase supplies and hire contractors; construction expenditures used to build long term assets; and expenditures used to purchase (rather than build) long term assets. See Pierson et al. (2015) for full definition of each of these components.

price index) did not see a significant decline in the affected counties relative to the control.

4.5 Was the Increase in Yields Localized or Pervasive?

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 alternative identification strategy that not only generalizes the findings to beyond the areas that were monitored, but also reaffirms the causal interpretation.

In firefighting, airports are *mandated* to use aqueous film-forming foams (AFFF), which primarily consist of PFAS (Part 139 Certification of Airports, 2004), owing to their excellent petroleum-based fire suppression properties. 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 conjecture that airports discharge PFAS into the ground regularly and have high potential to contaminate nearby areas.

We use airport presence as a proxy for PFAS contamination and examine how the offering yields of the municipalities within 40 miles of any airport changed after the event. We begin by estimating the following regression to validate the proxy:

$$\text{PFAS Contamination}_z = \beta_0 + \beta_1 \text{Airport}_{z \leq 40} + \theta_p + \varepsilon_z \,, \tag{6}$$

where the dependent variable is a zip code-level dummy for PFAS contamination, and the sample includes all zip codes. $Airport_{z\leq 40}$ indicates whether the zip code z is within 40 miles away from an airport; it is 1 if z is within a 40 miles radius around an airport and 0 otherwise. The coefficient of interest, β_1, captures the pollution effect of airports on nearby areas. In this regression, we control for airport fixed effects and cluster the standard error by airport as well. Panel (A) of Table (XI) shows that, as opposed to locations beyond 40 but within 50, 60, 70, and 80 miles away from an airport, locations within 40 miles have a 1% higher probability of contamination of drinking water. This validates the usage of airport proximity as proxy. [14]

Since 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 bonds issued by municipalities located near a U.S. airport:

$$\begin{aligned} \text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{Airport}_{z\leq 40} \times \text{ Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst}. \end{aligned} \tag{7}$$

Panel (B) of Table (XI) shows the regressions results. We see that the municipalities near airports witnessed an increase of 13–15 bps in offering yields. The estimates are robust if we compare the nearby area to a 50, 60, 70, and 80 mile donut area. All in all, this alternative method reaffirms and generalizes the conclusion from the DD analysis that the revelation of pollution led to higher offering yields of the general-purpose bonds.

4.6 Effect on Yields of Already-issued Bonds

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

[14] 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.

equation:

$$\text{Trd. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \alpha_{imcs} + \gamma_{sy} + \varepsilon_{imcst} \ , \tag{8}$$

where *Trd. Yld.*$_{imcst}$ is the volume weighted average trading yields in month t of bond i of municipality m in county c of state s. Here $Post_t$ takes the value of 1 for $t \geq$ August, 2016 and 0 for the earlier periods. The regression includes bond (CUSIP) fixed effects, α_{imcs}, and "*State*×*Year*" fixed effects, γ_{sy}. While *County Controls*$_{cst}$ are the same as in Equation (4), *Bond Controls*$_{imcst}$ include the bond's remaining maturity at the time of the transaction (in months), the number of trades in each month, monthly standard deviation of the bond's dollar transaction prices, and maturity matched treasury yields. Standard errors are double clustered by CUSIP and month.

Table (XII) reports the results. The sample included all transactions in Column (1), inter-dealer transactions in Column (2), and dealer-customer transactions in Column (3). The coefficients suggest that the trading yields of the affected municipalities increased by 7–9 bps relative to the unaffected municipalities. In essence, similar to what we saw in the offering yields, the patterns in the trading yields point to an increase in investors' perceived risk for polluted municipalities.

4.7 Supplementary Discussion

This section provides supplementary discussions that aid in interpreting previous results and also help in ruling out some alternative explanations.

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 smaller 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. However, the findings suggest otherwise and rule out this explanation.

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).

5 Conclusion

In this paper we show that the discovery of a PFAS contamination that may have occurred deep in the past has important economic consequences for the communities who uncover it in the present. Using a difference-in-differences approach and an instrumental variable method, we find that the discovery leads to an increase in financing cost from the bond markets for the municipal borrowers operating in the affected communities. It is unlikely that the estimated effects are due to some macroeconomic factors or state-level policy differences, since we compared the municipal bonds issued from contiguous counties within the same state. The contamination discovery also led to an increase in out migration from the contaminated counties to other counties of the same state and municipalities responded to increased borrowing costs by reducing the expenditure and public employment. Interestingly, the burden of increased financing cost falls even on the general obligation bonds, which are generally considered safe and are backed by the taxing power of the issuers.

The regulations related to PFAS continue to evolve and many of these are likely to enforce a low threshold on permissible PFAS contamination. This may lead to discoveries of new contamination sites that would require financing to clean the contamination and to install monitoring and abatement technologies. This paper sheds light on how these other contaminated communities could be impacted.

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Figure I: 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*).

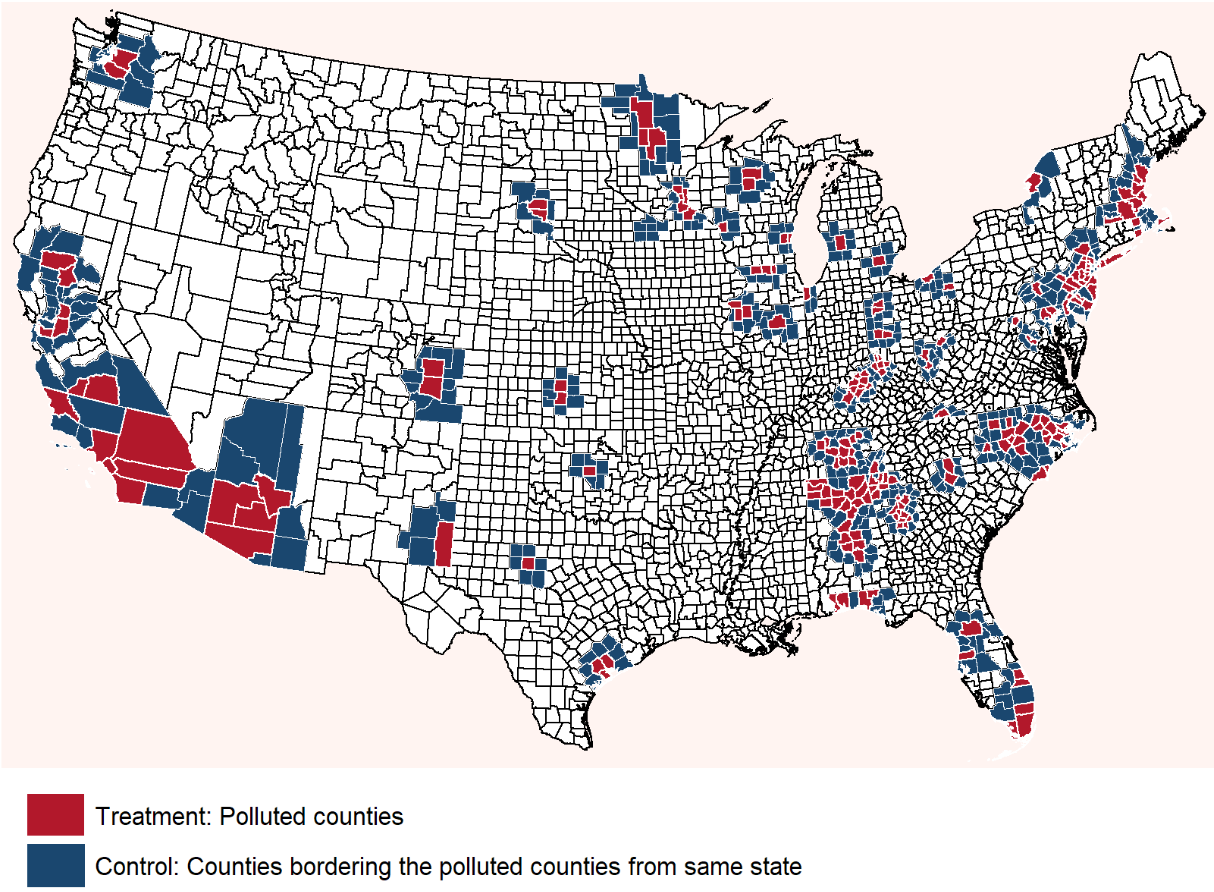


Figure II: Parallel Trends

Panel (A) of this figure plots the coefficients on β's from regressing the offering yield to maturity (YTM) using the following regression equation:

$$\begin{aligned}\text{YTM}_{imcst} = \alpha_0 + \textstyle\sum_{k=T-3}^{T-2} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \textstyle\sum_{k=T}^{T+2} \beta_k\ \text{Treatment}_{cs} \times \text{Year}_k \\ + \delta_1\ \text{Bond Controls}_{imcst} + \delta_2\ \text{County Controls}_{cst} + \text{Rating}_i + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst}\end{aligned}$$

where T = Event year 2016. $\text{Year}_k = 1$ if $t = T - k$. $\text{Year}_k = 0$ if $t \neq T - k$, k={-3,3}.

Panel (B) through (D) of this figure plots the coefficients from regressing the *County*×*Year*-level outcomes—growth rate of income per capita, employment, and property taxes per capita—using the following regression equation:

$$\begin{aligned}\text{Outcome}_{cst} = \alpha_0 + \textstyle\sum_{k=T-3}^{T-2} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \textstyle\sum_{k=T}^{T+2} \beta_k\ \text{Treatment}_{cs} \times \text{Year}_k + \\ \alpha_c + \gamma_{sy} + \varepsilon_{cst}\end{aligned}$$

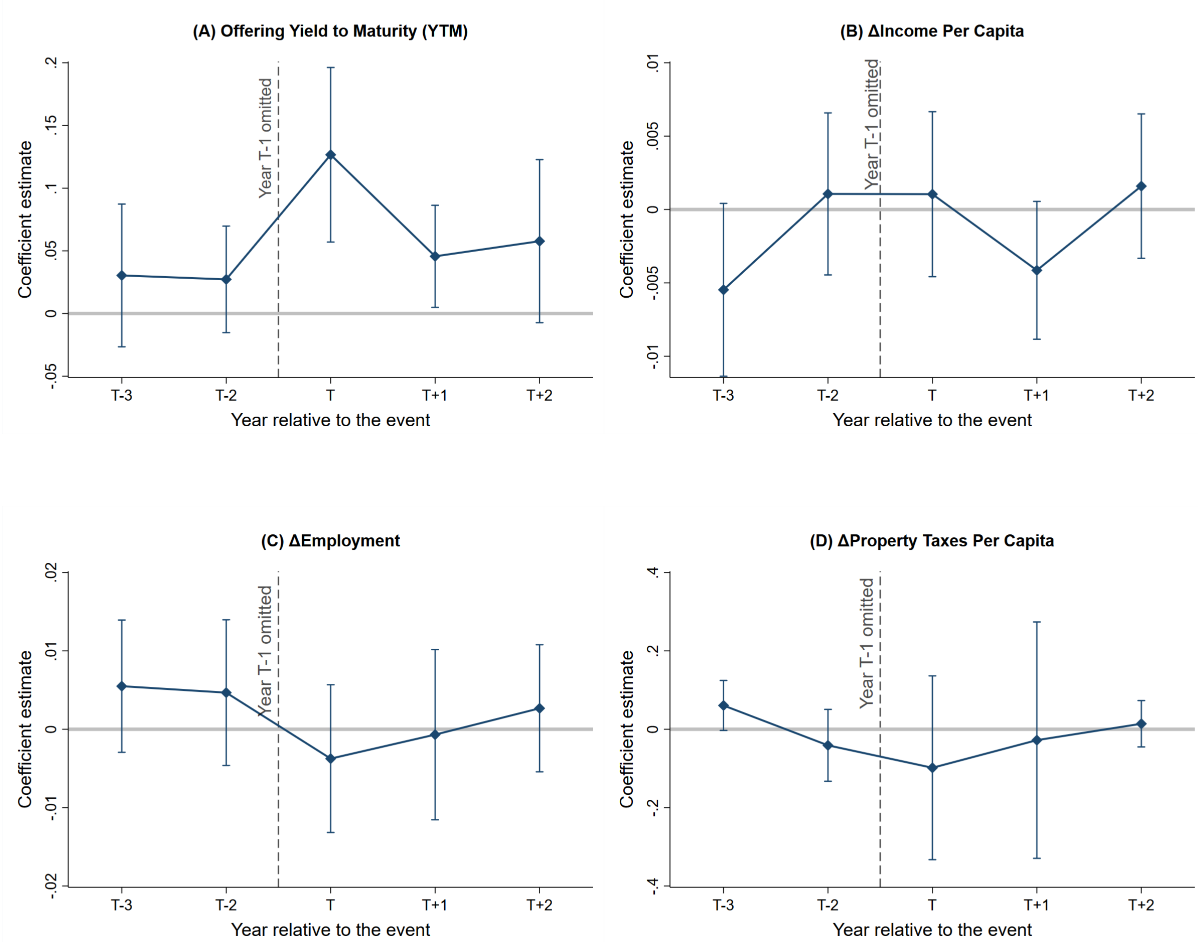
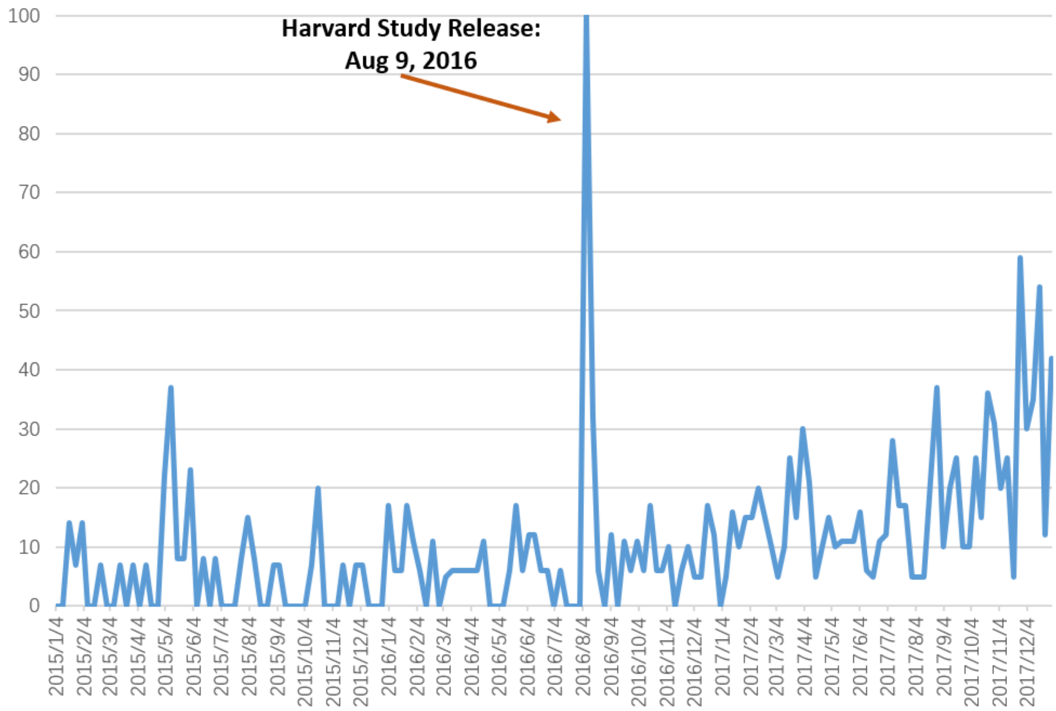


Figure III: The Event

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 cross-sectional average of Google Search Interest for the keyword "PFAS" coming from the contaminated states and non-contaminated states. The contaminated states refer to the 33 states mentioned in Hu et al. (2016). The averages were calculated for the two sets of states using the subregion search interest data (at state level) over every half-year time period from 2015 to 2018. The vertical dashed line marks in the plot 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

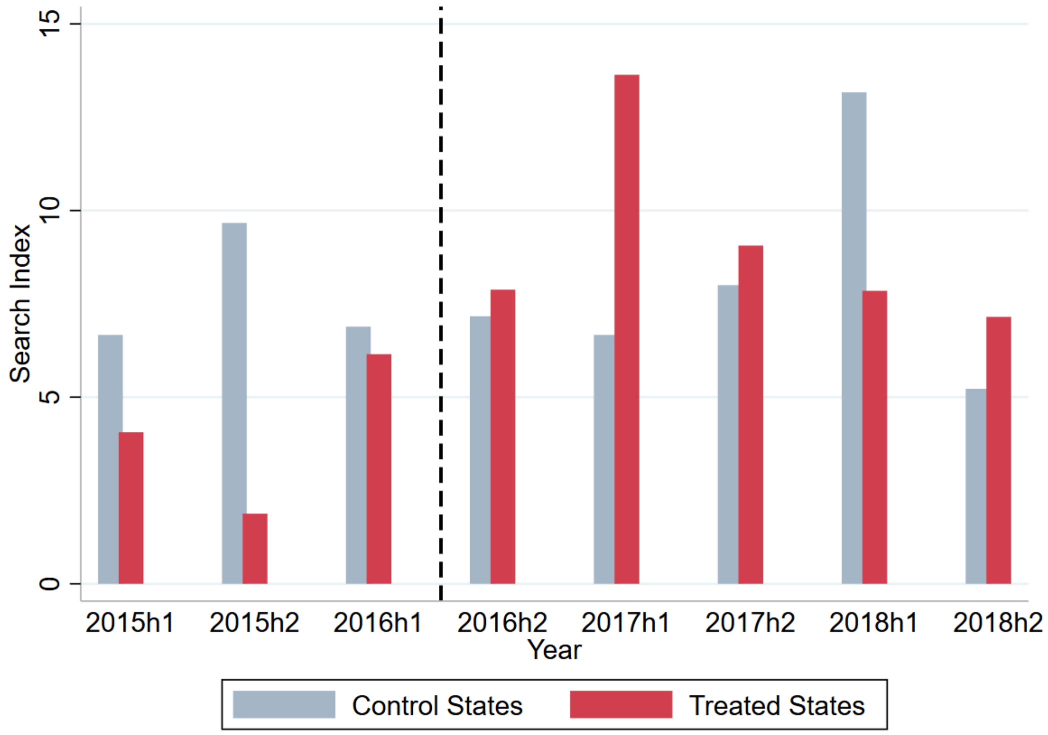


Table I: Major Developments Surrounding PFAS in the U.S.

This table summarizes major events realted to PFAS in the U.S. from 1940's till 2023. The details are adapted from Rich (2016, Jan. 6), Soechtig and Seifert (2018), The PFAS Project Lab (n.d.) and two court cases, In re E. I. Du Pont De Nemours & Co. C-8 Pers. Injury Litig. (2019) and Leach v. E. I. du Pont de Nemours and Company (2014).

	Before 2000
1940–1950	◦ 3M invented PFOA
	◦ DuPont purchased PFOA to produce Teflon
1999	◦ Lawsuit brought against DuPont (Tennant v. E. I. du Pont de Nemours and Company)
2000	◦ 3M ceased production of PFOA
	◦ DuPont started to manufacture PFOA on its own
	2001–2010
2001	◦ A class-action suit was filed against DuPont by 70,000 people in 6 water districts (Leach, et al v. E. I. DuPont de Nemours and Co.)
	◦ The EPA began investigation
2004	◦ DuPont settled the class-action suit
	◦ The C8 science panel was formed to evaluate if there was a "probable link" between PFOA and any diseases
2005	◦ The EPA fined DuPont $16.5 million
2009	◦ The EPA set a provisional limit of 0.4 ppb for short-term exposure
	◦ GenX, a short-chain PFAS, was introduced to replace PFOA
	After 2011
2011	◦ The C8 science panel started to publish reports linking PFOA to high cholesterol, ulcerative colitis, thyroid disease, testicular cancer, kidney cancer, and hypertension
	◦ Class members started to file personal injury suits (IN RE: E. I. du Pont de Nemours and Company C-8 Personal Injury Litigation)
2013–2015	◦ DuPont ceased production and use of PFOA
	◦ UCMR 3 testing of 6 PFAS (PFBS, PFHxS, PFHpA, PFOA, PFOS, PFNA) in all 4,064 public water supplies serving >10,000 individuals and 800 public water supplies serving <10,000 individuals
2016	◦ Apr, UCMR 3 data were released
	◦ May 19, the EPA set a Lifetime Health Advisory on PFAS of 70 ppt
	◦ Aug 9, the Harvard study was published
2017	◦ Feb, DuPont settled all the personal injury suits
	◦ Aug, the Pentagon tested drinking water of military installations and nearby communities
2018	◦ Mar, the Pentagon report was released
	◦ Jul 29, Michigan declared state of emergency for Kalamazoo county due to high concentrations of PFAS in drinking water
2019–2020	◦ Over 80 bills related to PFAS were introduced in the 116th Congress
2023	◦ 1,938 contamination sites discovered across the U.S. (The PFAS Project Lab).

Table II: Summary Statistics

Panel (A) of this table shows the number and percentage of detected polluted counties and concentration-level summary statistics. *N* indicates the number of counties that detected any of the six PFAS, i.e., PFOA, PFOS, PFHpA, PFHxS, PFNA, or PFBS. In total, 200 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)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	N	Affected(%)	Mean	SD	Min	Max	MRL
PFOA	128	64.00	48.50	58.03	20	349.00	20
PFOS	103	51.50	170.57	268.36	40	1800.00	40
PFHpA	94	47.00	23.77	20.13	10	86.91	10
PFHxS	64	32.00	149.40	164.17	32	730.00	30
PFNA	15	7.50	36.45	10.38	27	55.88	20
PFBS	14	7.00	170.00	86.74	100	370.00	90

Table II: Summary Statistics (continued)

Panel (B) of this table shows the summary statistics for the key variables and the difference in trends between the treatment and control group before the event. *YTM* 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 Moody's rating on a numerical scale that has the value 1 for an AAA rating and 26 for the lowest rating. *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. *Callable* is a dummy variable taking the value of 1 if the bond is callable and 0 otherwise. *Competitive Offering* is a dummy variable taking the value of 1 if the bond is offered competitively and 0 otherwise. *Trading Yield* denotes volume weighted average of trading yields (in percentages) for each bond in a month. *Monthly Num. of 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 *Income Per Capita*, Δ *Prop. Taxes Per Capita*, and Δ *Num. Employment* are the annual growth rates of per capita income, per capita property taxes, and the number of employment at the county level.

Panel B: Summary Statistics for Key Variables

	Full Sample				Difference in Trend over the Pre-event Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	Mean	Median	SD	Δ Treat (A)	Δ Control (B)	(A-B)	p-val
YTM(%)	273208	2.29	2.29	1.07	0.02	0.01	0.00	0.836
Issue Amt. (mn)	274442	3.77	0.76	16.62	0.23	0.33	-0.10	0.243
Coupon(%)	277877	3.42	3.25	1.28	0.11	0.11	0.00	0.888
Tenure(months)	278654	115.34	101.00	80.78	0.01	0.04	-0.02	0.374
Issue Rating	186571	3.87	3.00	2.28	0.01	0.00	0.00	0.950
Tax Exempt	278654	0.92	1.00	0.27	0.02	0.04	-0.02	0.276
Insured	278654	0.14	0.00	0.34	0.76	0.33	0.43	0.175
Callable	278649	0.43	0.00	0.50	0.03	0.06	-0.03	0.517
Competitive Offering	275026	0.56	1.00	0.50	0.08	0.06	0.01	0.843
Trading Yield (%)	2473576	2.36	2.24	1.15	-0.14	-0.15	0.02	0.131
Monthly Num. of Trades	2523939	7.79	4.00	18.08	0.07	0.04	0.03	0.391
Monthly SD of Price	2340711	0.69	0.56	0.62	-0.22	-0.22	-0.00	0.892
Δ Income Per Capita	2478	0.03	0.03	0.03	1.46	2.23	-0.76	0.689
Δ Prop. Taxes Per Capita	2460	0.05	0.02	1.07	-1.09	-1.22	0.13	0.501
Δ Num. Employment	2492	0.01	0.02	0.04	-1.20	-0.84	-0.37	0.506

Table III: PFAS Contamination and Offering Yields

This table reports the estimated treatment effects of pollution on offering yields of bonds issued by general-purpose municipalities. The regression specification follows Equation (4):

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

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, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.05**	0.07***	0.07***
	(2.36)	(3.46)	(3.36)
Controls	N	Bond	Bond & County
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.27	0.87	0.87
Observations	62681	62492	61926

Table IV: Heterogeneous Effects on Offering Yields by Repayment Obligation

This table reports the estimated treatment effects of pollution on offering yields of general obligation (G.O.) bonds (in Column 1) and revenue bonds (in Column 2) and tests their difference (in Column 3). 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. *G.O.* is an indicator for general obligation bonds. 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. The coefficient associated with $Treatment_{cs} \times Post_t \times G.O.$ captures the differential impact on G.O. versus revenue bonds. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

	G.O. Bonds	Non-G.O. Bonds	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.06***	0.11**	0.10**
	(2.72)	(2.16)	(2.51)
Treat × Post × G.O.			-0.08*
			(-1.83)
Treat × G.O.			0.03
			(0.69)
Post × G.O.			0.10***
			(4.57)
G.O.			-0.03
			(-1.13)
Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.88	0.85	0.87
Observations	47076	14821	61926

Table V: Heterogeneous Effect on Offering Yields by Bond Rating

Panel (A) of this table reports the estimated treatment effects of pollution on offering yields of bonds by Moody's ratings. Ratings of AA3 and above (≤ 3 on a numeric scale) are classified as high. 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. The coefficient associated with $Treatment_{cs} \times Post_t \times High\ Rating$ captures the differential impact on bonds of high and low ratings. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

Panel A: Contemporaneous Bond Rating

	Low Rating	High Rating	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.08	0.06**	0.11***
	(1.64)	(2.48)	(2.62)
Treat × Post × High Rating			-0.12**
			(-2.48)
Post × High Rating			0.11***
			(4.24)
Treat × High Rating			0.14
			(1.52)
Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.86	0.88	0.87
Observations	15557	28882	44450

Table V: Heterogeneous Effect on Offering Yields by Bond Rating (continued)

Panel (B) of this table reports the estimated treatment effects of pollution on offering yields of bonds by Moody's pre-period ratings. In this panel, high and low ratings are classified by issuer's pre-event average rating. 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. The coefficient associated with $Treatment_{cs} \times Post_t \times$ *High Rating* (*ex-ante*) captures the differential impact on bonds issued by municipalities with high and low ex-ante ratings. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

Panel B: Ex-ante Issuer Rating

	Low Rating	High Rating	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.08	0.07***	0.10*
	(1.60)	(2.63)	(1.97)
Treat × Post × High Rating (ex-ante)			-0.09*
			(-1.76)
Post × High Rating (ex-ante)			0.13***
			(4.68)
Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.86	0.88	0.87
Observations	9089	35195	44284

Table VI: Heterogeneous Effects on Offering Yields by Bond Maturity

This table reports the estimated treatment effects of pollution on offering yields of municipal bonds of short maturities (≤ 10 years) in Column (1) and of long maturities (> 10 years) in Column (2) and their tested difference in Column (3). 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. The coefficient associated with $Treatment_{cs} \times Post_t \times Long\ Maturity$ captures the differential impact on bonds of long and short maturities. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

	Short Maturity	Long Maturity	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.05***	0.05**	0.13***
	(2.83)	(2.05)	(5.61)
Treat × Post × Long Maturity			-0.08***
			(-2.93)
Treat × Long Maturity			0.08***
			(3.53)
Post × Long Maturity			-0.31***
			(-13.17)
Long Maturity			0.24***
			(10.66)
Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.87	0.84	0.88
Observations	37764	24098	61926

Table VII: Heterogeneous 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 nine states that have policies to support distressed municipalities (ME, MI, NC, NJ, NV, NY, OH, PA, and RI) and from the 19 states which allow full or conditional access to Chapter 9 bankruptcy provisions (AL, AZ, AR, CA, CO, CT, FL, ID, IL, KY, LA, MN, MO, MT, NE, OK, SC, TX, and WA). We refer to the first group by *Proactive* states and the second *Ch. 9 Bankruptcy* states. 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. The coefficient associated with $Treatment_{cs} \times Post_t \times Proactive$ captures the differential impact on bonds issued in proactive and Chapter 9 states. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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.

	Proactive States	Ch. 9 Bankruptcy States	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.04	0.09***	0.09***
	(1.24)	(2.66)	(2.61)
Treat × Post × Proactive			-0.08*
			(-1.79)
Post × Proactive			0.08**
			(2.28)
Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.86	0.87	0.87
Observations	26336	17375	43711

Table VIII: Ex-ante Fiscal Distress

This table reports the estimated treatment effects of pollution on offering yields of bonds by county's interest coverage ratio, which is defined as the ratio of net revenue over interest expense. If a county had above median interest coverage ratio before 2016, we say it had low interest burden ex ante. 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. The coefficient associated with $Treatment_{cs} \times Post_t \times$ *Low Interest Burden* captures the differential impact on bonds issued in counties with ex ante low and high interest burden. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the per capita income growth rate, property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). 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 Interest Burden	Low Interest Burden	Interaction Effect
	(1)	(2)	(3)
	YTM	YTM	YTM
Treat × Post	0.11***	0.04*	0.11***
	(3.02)	(1.71)	(3.87)
Treat × Post × Low Interest Burden			-0.11***
			(-3.00)
Post × Low Interest Burden			0.09***
			(4.42)
Bond & County Controls	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y
Cluster: County	Y	Y	Y
R^2 (Adj.)	0.88	0.87	0.87
Observations	21128	40741	61870

Table IX: Shrinking Economic Base

This table reports the estimated treatment effects of pollution on county net out-migration within state (in Columns 1 and 2) and outside state (in Columns 3 and 4) following the framework:

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

County Net Out-migration is the county-level net outward migration calculated as percentages of population. $Treatment_{cs}$ 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 $t \geq 2016$ 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. $County\ Controls_{cst}$ include the per capita income growth rate, property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). All regressions include county and 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.

	Within State Net Out-mirgration from County (% of population)	
	(1)	(2)
Treat × Post	0.10**	0.11**
	(2.15)	(2.29)
Controls	N	Y
FE: County, Year	Y	Y
Cluster: County	Y	Y
R^2 (Adj.)	0.58	0.61
Observations	3752	3512

Table X: How Municipalities Responded?

This table reports the estimated treatment effects of pollution on public expenditure and employment at the county level following the framework:

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

Total Public Expenditure is expressed as *per capita* dollar amounts aggregated to the county level.*Public Employment* refers to full-time equivalent public sector employment, measured per 1,000 population. $Treatment_{cs}$ 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 $t \geq 2016$ 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. $County\ Controls_{cst}$ include the county-year level growth rates of per capita income and per capita property taxes in Column (3) and (4), and the number of employment growth rate in addition in Column (1) and (2). All variables are defined in Panel (B) of Table (II). All regressions include county and 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.

	Total Public Expenditure (USD per capita)		Public Employment (per 1000)	
	(1)	(2)	(3)	(4)
Treat × Post	-155.90***	-156.81***	-2.65***	-2.60***
	(-2.76)	(-2.71)	(-5.44)	(-5.29)
Controls	N	Y	N	Y
FE: County, Year	Y	Y	Y	Y
Cluster: County	Y	Y	Y	Y
R^2 (Adj.)	0.96	0.97	0.86	0.86
Observations	3609	3516	3084	3008

Table XI: Airports as Potential PFAS Contamination Source and Offering Yields

Panel (A) of this table reports the estimates from regressing contamination status on airport proximity:

$$\text{PFAS Contamination}_z = \beta_0 + \beta_1 \text{ Airport}_{z \leq 40} + \theta_p + \varepsilon_z \, .$$

Here z denotes zip codes. The regression sample includes all the zip codes in the U.S. that are within 40, 50, 60, 70, and 80 miles of airports. $Airport_{z \leq 40}$ is a dummy variable equal to 1 if zip code z is within 40 miles of an airport, and 0 if it is beyond 40 miles but within 50 (Column 1), 60 (Column 2), 70 (Column 3), or 80 (Column 4) miles of any airport. The outcome variable is an indicator for whether there was PFAS contamination in zip code z. θ_p captures airport fixed effects. Standard errors are clustered by source airport. t-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 Airports

	Sample: 50 Mile	Sample: 60 Mile	Sample: 70 Mile	Sample: 80 Mile
	(1)	(2)	(3)	(4)
	Polluted	Polluted	Polluted	Polluted
Within 40 Mile (=1)	0.01***	0.01***	0.01***	0.01***
	(3.35)	(3.95)	(4.18)	(4.18)
FE: Airport	Y	Y	Y	Y
Cluster: Airport	Y	Y	Y	Y
R^2 (Adj.)	0.06	0.06	0.06	0.06
Observations	28058	30147	31386	32167

Table XI: Airports as Potential PFAS Contamination Source and Offering Yields (continued)

Panel (B) of this table shows the change in offering yields of bonds issued by municipalities near relative to far from an airport before and after the event. The regressions are estimated using various donut areas as the control group. The specification follows Equation (7):

$$\text{Off. Yld.}_{imcst} = \beta_0 + \beta_1 \text{ Airport}_{z\leq 40} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} + \delta_2 \text{ County Controls}_{cst} + \alpha_{mcs} + \gamma_{sy} + \varepsilon_{imcst} \ .$$

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. $Airport_{z\leq 40}$ is a dummy variable equal to 1 if zip code z is within 40 miles of an airport, and 0 if it is beyond 40 miles but within 50 (Column 1), 60 (Column 2), 70 (Column 3), or 80 (Column 4) miles of any airport. $Post_t$ takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with $Airport_{z\leq 40} \times Post_t$ captures the change in the dependent variable before and after the event in areas near relative to far from any airport. $Bond\ Controls_{imcst}$ include the bond's issuance amount, tenure, the Moody's rating of the issue, whether the bond is federal tax exempt, insured, callable, and competitively offered; and $County\ Controls_{cst}$ include the per capita income growth rate, property taxes, and the number of employment at the county-year level. All variables are defined in Panel (B) of Table (II). All regressions include municipality fixed effects and "*State*×*Year*" fixed effects. Standard errors are clustered by source airport. 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 around Airports

	Sample: 50 Mile	Sample: 60 Mile	Sample: 70 Mile	Sample: 80 Mile
	(1)	(2)	(3)	(4)
	YTM	YTM	YTM	YTM
Within 40 Mile (=1) × Post	0.15***	0.14***	0.14***	0.13***
	(4.79)	(4.76)	(4.65)	(4.56)
Controls	Y	Y	Y	Y
FE: Issuer, State × Year, Rating	Y	Y	Y	Y
Cluster: Airport	Y	Y	Y	Y
R^2 (Adj.)	0.88	0.88	0.88	0.88
Observations	49688	50609	50778	50909

Table XII: Treatment Effect on Trading Yields

This table reports the estimated treatment effects of pollution on trading yields of municipal bonds. The regression specification follows Equation (8):

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

The outcome variable is the volume-weighted average transaction yield (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. The coefficient associated with $Treatment_{cs} \times Post_t$ captures the change in trading yields before and after the event in treated counties relative to bordering control counties in the same state. $Bond\ Controls_{imcst}$ include bond's remaining maturity at the time of transaction (in months), the number of trades in each month, monthly standard deviation of the bond's dollar transaction prices, and maturity matched treasury yields; $County\ Controls_{cst}$ include the growth rates of per capita income, per capita property taxes, and the number of employment at the county-year level. All variables are defined in Table (II). All regressions include CUSIP fixed effects and "$State \times Year$" 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.

	(1)	(2)	(3)
	Trading Yield (All)	Trading Yield (Inter-dealer)	Trading Yield (Dealer-customer)
Treat × Post	0.08***	0.07***	0.09***
	(3.53)	(3.12)	(3.79)
Controls	Y	Y	Y
FE: Cusip, State × Year	Y	Y	Y
Cluster: Cusip, Year-month	Y	Y	Y
R^2 (Adj.)	0.87	0.87	0.85
Observations	1351161	1071212	1345643