Municipal and Economic Consequences of PFAS Contamination Discovery*

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Abstract

We show that discovery of contamination by pollutants that are unmonitored and unregulated adversely affects local municipal finances and economic conditions. We causally document a 9-basis-points increase in primary market yields of municipal bonds from the counties where per- and polyfluoroalkyl substances (PFAS) contamination was discovered for the first time, vis-à-vis the bonds from bordering, uncontaminated, same-state counties. The yields increased more for riskier bonds. We link the increased yields to a reduction in allocation by mutual funds and banks in the municipal bonds from the affected counties. These counties subsequently experienced heightened out-migration and depressed public expenditure and employment.

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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*)

In this paper we examine the effects of contamination by a unique set of unregulated and unmonitored pollutants, known as per- and poly-fluoroalkyl substances (PFAS), on local economic outcomes. Global attention has been growing on PFAS due to their long-lasting widespread environmental contamination and adverse health effects (Abunada, Alazaiza, and Bashir, 2020; Ahrens and Bundschuh, 2014). Since these are unregulated and unmonitored pollutants, unique economic challenges emerge when contamination by such chemicals is discovered and requires remediation. By mid-2023, 1,153 locations across the U.S. have been found to be contaminated by the two most widespread PFAS, perfluorooctanoic acid (PFOA) and perfluorooctane sulfonicacid (PFOS) (PFAS Project Lab, 2023a), despite these chemicals having been largely phased out from the U.S. since around 2008 (ATSDR, 2021, p.654). Difficulties in remediation arise from several reasons. The source of contaminant discharge on which liabilities could be imposed is unclear in many of these cases, because these chemicals have been used in numerous consumer and industrial applications over a long period of time and any or all entities could potentially contribute to the contamination.[1] Moreover, since these were unregulated, their usage was not restricted and enforceable safe exposure limits did not exist, making it difficult to recover damages through regulatory penalties and even with costly litigation.[2] It is thus important to understand the effects that such contamination discoveries—akin to receiving unexpected toxic inheritance—have on local economic outcomes.

Motivated by the facts surrounding contamination by PFAS, in this paper we examine the causal link between the PFAS contamination discovery and the municipal

[1] Consider for example the statement from Zone 7 Water Agency of City of Pleasanton, where drinking water was contaminated by PFAS: "Maybe some [of PFAS came] from a landfill, maybe some from the airport, maybe some from people doing laundry of their water-repellent clothes. I doubt that we're going to find one or two organizations to go after." (& the West, Stanford University, June 10, 2020)

[2] While more than 15,000 nationwide claims related to PFAS contamination are ongoing against DuPont, Chemours, Corteva, and 3M, the major manufacturers of PFAS, and while these companies have paid more than $11.5 billion for damages (TIME, June 12, 2023), considerable uncertainties remain regarding available remedies (& the West, Stanford University, June 10, 2020).

finances of the affected areas. The discovery of contamination requires remediation, clean up, and installation of abatement technologies, which are overseen by municipalities for whom bond markets are an important source of capital. We focus our analysis on assessing the changes in offering yields to maturities (primary market yields) of their bond borrowings, which are directly tied to their financial repayment obligations. This is relevant given that financial constraints of municipalities adversely affect local employment and growth (Adelino, Cunha, and Ferreira, 2017; Dagostino, 2018) and quality of public services (Yi, 2020; Agrawal and Kim, 2021).

We report three key findings. First, the primary market yields of new municipal bonds issued from affected areas increased relative to the bonds from the bordering same-state counties that were uncontaminated. Second, we find that this increase was due to both a decrease in mutual fund allocation in the number and dollar amount of municipal bonds issued from contaminated counties and a reduction in municipal bond holdings by banks with significant presence in those areas. Finally, the contaminated counties subsequently saw a reduction in per capita public expenditure and employment, and heightened net out-migration and in-flow of lower income population.

To arrive at these causal findings, we utilize the first-time discovery of PFAS contamination sites across the U.S. in 2016 in a difference-in-differences (DD) strategy. From 2013 to 2015, 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, the testing revealed that 200 counties across 33 states had their water supply systems contaminated with the PFAS. We classify these counties as treated in our DD strategy. The counties bordering these treated counties from the same state that were uncontaminated are classified as control. Our sample period runs from 2013 to 2018.

We use this discovery of contamination sites in 2016 as an event that revealed the contamination status of the counties, where the contamination itself occurred in the *past* and the reasons remain largely unknown and uncertain.[3] Several features make

[3] We cannot provide a definitive answer to why some counties were contaminated and others not, but we note that the scientific understanding of how PFAS accumulates in the environment is still evolv-

the revelation of the PFAS contamination of the counties mimic an exogenous event. First, these substances had not been regulated or monitored prior to this event. Second, considerable uncertainties existed on what technology to use to detect PFAS in water, as technical standards were unavailable (Dorrance, Kellogg, and Love, 2017) and procedures had limited sensitivity (EPA, Jan 2017). Third, safe limits for the concentration of these chemicals in drinking water did not exist. This undermined any incentives of privately-funded testing of drinking water for PFAS. The high cost of PFAS sampling and testing—about $87 million under the UCMR (3) program (U.S. Government Accountability Office, 2014)—acted as another deterrence.

We are careful not to claim that the contamination discovery was exogenous to all observable or unobservable characteristics of the counties. However several diagnostic tests support the unpredictability of the contamination status and an absence of pre-tends. Using yearly data from 1998 until 2015, we test whether the share of PFAS-related industries and the quality of drinking water infrastructure in a county could predict the contamination status in 2016, and find no correlations. A range of county-level economic variables—growth rate of employment, establishments, per capita property taxes, or intergovernmental revenues—exhibited no discernible differences in pre-tends between the treated and control counties. There is also no statistical difference in the growth rate over the pre-event time period for all the variables used in our analysis measured across treated and control counties. Furthermore, since both treated and respective control counties are from the same states, they are subject to the same state-level fiscal and municipality-related policies. By design, DD estimates difference out the contribution of national or state-level factors in the outcome variables, such as gubernatorial elections or the 2016 presidential election. Finally, several other studies rely on a similar empirical strategy to derive causal estimates (Gormley and Matsa, 2011; Lam, 2022; Di Maggio et al., 2017; Fuster and Willen, 2017; Gupta, 2019).[4]

ing (Abunada et al., 2020; Ahrens and Bundschuh, 2014), and the anecdotal statement in Footnote (1) exemplifies this difficulty.

[4] Gormley and Matsa (2011) and Lam (2022) utilize the discovery of carcinogen status of chemicals, where the affected firms are those who decided in the past to use those chemicals. Similarly, Di Maggio et al. (2017), Fuster and Willen (2017), and Gupta (2019) use contemporary changes in interest rates as

We begin the discussion by focusing on the salience of the event. We find that the revelation of the contamination was a shock and received widespread publicity (The Harvard Gazette, Aug 9, 2016; Hu et al., 2016). Google searches for the keyword "PFAS" from the U.S. surged. Second, the costs to install the infrastructure needed to treat drinking water to remove PFAS were estimated to be significant.[5] Third, in addition to these direct costs, contamination discovery also resulted in lost economic opportunities. For example, the redevelopment plan of the former Willow Grove military base and the surrounding areas in Pennsylvania was withdrawn after PFAS contamination was discovered (The Philadelphia Inquirer, Nov 20, 2019). In summary, these features together suggest that the contamination discovery was a salient event.

Our baseline estimates comparing primary market offering yields on municipal bonds suggest that the issuers from the polluted counties suffered an average increase of 8–9 basis points (bps) in offering yields to maturities vis-à-vis the issuers from the bordering uncontaminated counties from the same state. This is a considerable increase, given that if the credit rating of the bonds had dropped by two notches from Aaa to Aa2, the yields would have risen by only about 6 basis points on average. Our estimates are robust to the inclusion of a host of controls for bond characteristics and county-level economic conditions, and granular fixed effects including bond rating, bond's capital type, county, and state $\times$ year.

To explain the increase in the offering yields of new municipal bonds, we propose a mechanism similar to the one in Chordia, Jeung, and Pati (2022): contamination dis-

exogenous reductions in monthly repayments of households who decided in the past to obtain adjustable rate mortgages, instead of fixed rate mortgages.

[5] Given the lack of concentration standards for PFAS and unavailability of technical standards for testing and cleanup procedures, estimates of the clean-up and abatement cost vary widely. American Water Works Association estimated that removing PFOA and PFOS nationwide would cost from $3 billion to $38 billion depending on the allowable concentration of these chemicals in drinking water (ranging from 70 ng/L to 20 ng/L). In addition, installing treatment technology nationwide would require more than $370 billion in capital investment and over $12 billion in annual operational and maintenance costs (AWWA, 2019). Anecdotally, drinking water treatment equipment to remove a type of PFAS in the Brunswick county, North Carolina was estimated to require about $100 million in investment and $3 million in annual maintenance (National Association of Counties, Apr 15, 2019). Safer States (February 2019) provides several other examples. The New York Department of Health estimated that infrastructure upgrades worth $855 million and annual operating costs worth $40 million would be needed 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)

covery affects municipal default risk through worsening economic outcomes, as it leads to (i) an unexpected increase in infrastructure investments and clean up related operational expenses for the municipalities;[6] and (ii) a reduction in their future expected revenues arising from worsening out-migration, public expenditure and employment–an effect further compounded by the fiscal multiplier effect of local municipal expenditure (Dagostino, 2018; Adelino et al., 2017). These potentially lead to imbalances in their current and future operational budgets. Since municipalities are expected to balance their operational budgets and require voter approval to raise long-term borrowing, which is subject to restrictions contained in statutes, charters, and state policies (Ang, Green, Longstaff, and Xing, 2017; Haughwout, Hyman, and Shachar, 2021), their default risk could rise after the event, leading to higher offering yields. We provide empirical evidence in favor of both of these hypotheses.

Evidence in support of the default risk hypothesis comes from a series of cross-sectional tests examining the differential increase in offering yields of bonds with characteristics that the literature on municipal finance commonly associates with risk (K. R. Cornaggia, Hund, Nguyen, and Ye, 2021; K. Cornaggia, Li, and Ye, 2022; Gao, Lee, and Murphy, 2020). We analyze the sub-samples of (i) bonds that are not backed by taxation power and others; (ii) long and short maturity bonds; (iii) high and low fiscal dependence of county revenues on inter-governmental transfers in the pre-event period; (iv) low and high homeownership rate; and (v) bonds from states without and with proactive support for distressed municipalities. In each comparison, the increase in yields was larger for the first sub-sample, supporting the default risk explanation.

To further understand the source of the rise in the offering yields after the contamination discovery, we take a novel approach of examining the changes in supply of capital by two institutional investors shown to be important for municipal bond pricing—mutual funds (Y. Li, O'Hara, and Zhou, 2023; Adelino, Cheong, Choi, and

[6] For example, to address PFAS contamination, the City of Westfield from Hampden County, Massachusetts—a treated county in our sample—approved USD 13 million bonds (Hope E. Tremblay, Jun. 29, 2018).

Oh, 2023) and banks (Yi, 2020; Bergstresser and Orr, 2014; Ivanov and Zimmermann, 2019). We find that percentage allocation and the number of bonds (in natural log) held by active mutual funds in bonds of the municipal issuers from the contaminated counties decreased by 0.37 basis points and 1.4 percentage points respectively relative to those of the issuers from the control counties. Similarly, banks with larger deposits in the contaminated counties reduced holdings of municipal securities. Moreover, since institutional investors are considered sophisticated, the reductions in their capital allocation indicate that the rise in the offering yields was not merely driven by sentiments.

To guide our examination of adverse economic impact hypothesis, we draw upon the argument from J. Cornaggia, Gustafson, Israelsen, and Ye (2019) and Hastie (1972), who suggest that an increase in out-migration may lead to a contraction in the taxable economic base, thereby affecting the municipal bond yields. We find that the affected counties experienced higher net out-migration than the bordering control counties. More importantly, while the income levels of the out-migrating population were similar to those of the stayers, the incoming population had lower income levels, resulting in a decrease in county-level taxable personal income. We also find that at the county-level, per capita municipal expenditure declined by 3.1%, public employment by 9%, and the share of public employment (in total employment) by 1 percentage point in the affected counties relative to the control. Such reductions have been shown to be detrimental for local economic growth (Adelino et al., 2017; Chava, Malakar, and Singh, 2023; Dagostino, 2018).

Overall, we contribute to several strands of the literature. We show that discovering PFAS contamination that may have occurred in the past leads to deteriorating local economic outcomes, in which municipal bond markets play a role. This paper is the first to examine effect of unregulated contaminants on local economic and municipal outcomes. We contribute to the literature that highlights the link between the municipal bond markets and the real outcomes (Agrawal and Kim, 2021; Yi, 2020; Jerch, Kahn, and Lin, 2020; K. R. Cornaggia et al., 2021; W. Li and Zhu, 2019; Butler and Yi, 2018). Several other factors have been shown to affect municipal finances, such as tax advantage (Garrett, Ordin, Roberts, and Suárez Serrato, 2023), municipal contracting restrictions (Garrett and Ivanov, 2022), natural disaster (Auh, Choi, Deryugina, and Park, 2022), 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), 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 et al., 2023), 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).

Our findings that mutual funds and banks reduce capital to the affected municipalities speaks to the new literature linking demand from institutional investors to corporate bond prices (Cai, Han, Li, and Li, 2019; Ivashina and Sun, 2011; Nikolova, Wang, and Wu, 2020) and municipal bond yields (Adelino et al., 2023; Y. Li et al., 2023). This finding also align with the implications of the demand-system based asset pricing models (Bretscher, Schmid, Sen, and Sharma, 2022; Koijen and Yogo, 2019).

We also add to the literature studying effects of PFAS in particular and water pollution in general. In a hyperlocal study of PFAS contamination of Paulsboro water system of New Jersey, Marcus and Mueller (2023) find that house prices decline after the contamination. We show on a larger scale using county boundaries that discovery of PFAS contamination makes municipal borrowings expensive and causes increased out-migration and reduced municipal expenditure and public employment. Other studies related to water pollution show that lead in drinking water reduces consumer credit scores (Gorton and Pinkovskiy, 2021), increases healthcare demand (Danagoulian, Grossman, and Slusky, 2020), and depletes housing stock and raises public expenditure (Christensen, Keiser, and Lade, 2019). Muehlenbachs, Spiller, and Timmins (2015) show that groundwater contamination leads to depressed house prices.

1 Institutional Information and Research Design

1.1 The PFAS

PFAS are a family of thousands of synthetic chemicals, about 4,730 currently on record (Abunada et al., 2020). Among them, PFOS and PFOA were the earliest to be developed, have the longest manufacturing history, and are the most thoroughly understood. 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 (Glüge et al., 2020). These are highly toxic and extremely soluble in water, and are often known as "Forever Chemicals" because they are incredibly resistant to environmental degradation, so much so that it has not been feasible to detect how long they take to naturally degrade by half in the environment (NIEHS, 2019, p.1). These chemicals 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.), reproductive health (Waterfield, Rogers, Grandjean, Auffhammer, and Sunding, 2020) and infant health (Liu et al., 2023; Padula et al., 2023). Table (I) summarizes key events related to PFAS in the U.S.[7]

[Insert Table (I) About Here]

1.2 The Event and Difference-in-Differences Design

Drinking water supplies in the U.S. were never tested for PFAS on a national scale until the third Unregulated Contaminant Monitoring Rule (UCMR 3). The testing of drinking water for contamination by PFAS under this program took place across the U.S. from January 2013 to December 2015 (Federal Register, May 2, 2012, Exhibit 3: Time-

[7] Dorrance et al. (2017) provide a non-technical discussion of PFAS' manufacturing history, chemical properties and remediation challenges. Johnson (2020) provides a discussion of regulatory challenges around it; and DeWitt et al. (2015) provides a comprehensive technical discussion of its health effects.

line of UCMR Activities). This program tested for six PFAS chemicals: PFOA, PFOS, PFHpA, PFHxS, PFNA, and PFBS.[8] Relying on the data from the program, Hu et al. (2016) identified PFAS contamination across the U.S. This was one of the first to systematically reveal the contamination and made headlines (The Harvard Gazette, Aug 9, 2016). Panel A of Figure (I) shows one example. With this publicity, search activity on Google arising from across the U.S. about the keyword "PFAS" spiked, as Panel B of Figure (I) illustrates.[9] Even though these searches reflect the views of the overall U.S. population, not of the municipal investors, these are informative, because retail investors hold about 44% of the outstanding municipal bonds.

[Insert Figure (I) About Here]

We employ a DD design around the detection of PFAS in drinking water under the UCMR (3) program. The treatment group consists of the 200 counties from 33 states where PFAS were detected. The control group consists of 426 such counties which share border with the contaminated counties and lie within the same state, but were not detected to have PFAS contamination. Figure (II) shows these counties on the map of the contiguous U.S. All local governments, municipalities, and other public issuers located in a county are assigned the treated or control status based on the county. August 9, 2016 serves as the event date. Our sample runs from 2013 till 2018. This strategy to compare within-state bordering counties is a variation of the empirical strategy used in Dube, Lester, and Reich (2010).

[Insert Figure (II) About Here]

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

[9] 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.

1.3 Could Industrial Activities or Infrastructure Quality Predict the Contamination?

Exogeneity of the contamination locations is essential to uncover causal estimates of the event. While we acknowledge that the PFAS contamination likely did not occur exogenously, but we test for two factors commonly understood to cause PFAS contamination: the presence of PFAS-releasing industries and quality of local drinking water infrastructure. To measure the local industries related to PFAS, a complete list of industries related to PFAS is required, but since these chemicals were unmonitored and unregulated, such a list is not available at the time of the event. We thus rely on monitoring requirement that became mandatory after the event. From the year 2020, the Toxics Release Inventory (TRI) data compiled by EPA started recording whether an establishment discharges PFAS. We compiled the list of all three-digit NAICS industry codes of all the establishments that reported discharging PFAS in the years 2020 and 2021. Using these industry codes and data on the number of establishments from County Business Patterns, we calculated a county-level annual measure of PFAS industry share equal to the ratio of the number of establishments belonging to these three-digit industry codes to the total number of establishments in a county. We then regress the *Treatment* dummy on the PFAS share annually from 1998 till the pre-event year 2015 for all the counties in the sample. We begin this analysis in 1998, because this is the earliest year since when the "county×NAICS×year" data become available in the County Business Patterns. The regression equation is:

$$\text{Treatment}_{cs} = \alpha_0 + \beta_1 \times \text{PFAS-share}_{cs} + \gamma_s + \epsilon_{cs}. \tag{1}$$

Here $Treatment_{cs}$ takes the value of 1 if a county c from state s was discovered to have PFAS contamination in 2016. Panel (A) of Figure (III) shows the coefficients β_1 for each year and the 95% and 99% confidence intervals based on standard errors clustered at the state level. We see that the share of these industries in a county in any of the years up to 18 years prior to the event does not predict the contamination at the 95% confidence interval.

We repeat this analysis with the quality of drinking water infrastructure in a county. We measure the infrastructure quality by the number of annual county-level per capita health-related violations of drinking water code.[10] We regress *Treatment* dummy on this measure using the same regression equation and plot the coefficients β_1 and confidence intervals in Panel (B) of Figure (III). The estimates suggest that the quality of drinking water infrastructure do not predict the contamination either.

[Insert Figure (III) About Here]

The lack of prediction power of these two measures assures that the contamination status was not straightforward to predict. Nonetheless, recognizing the non-exogenous nature of the contamination and in abundance of caution, we include contemporaneous county-level share of PFAS industries and quality of drinking water infrastructure in all our regressions as control variables.

1.4 The DD Estimator

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

$$\begin{aligned} Y_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \delta \text{ Controls}_{imcst} + \text{Rating}_i + \text{Rating Agency}_i \\ + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst} \ , \end{aligned} \tag{2}$$

where Y_{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.[11] $Controls_{imcst}$ vary across specifications and consist of a host of bond characteristics and county-level economic indicators.

[10] Following Agrawal and Kim (2021), we define three type of violations as health-based: maximum contaminant level violations, maximum residual disinfectant level violations, and water treatment technique violations.

[11] In staggered DD designs, TWFE estimator suffers from "negative weights" issue (Borusyak, Jaravel, and Spiess, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2020), because the treatment effects could be heterogeneous (Goodman-Bacon, 2021) and TWFE estimates the average of the individual treatment effects weighted by variance. Since our research design involves a *single treatment*, not staggered, the issue of heterogeneous treatment effect across time does not arise.

$Rating_i$ and *$Rating\ Agency_i$* represent bond's numerical rating fixed effects and the rating agency fixed effects. These account for the fixed differences in the outcome variable for bonds rated differently and rated by different agencies. *$Capital\text{-}type_i$* represents the fixed effects for the type of capital, the two most types being "New Filing" and "Refunding". α_{cs} represents county fixed effects. These account for any inherent time-invariable differences across counties. γ_{st} denotes *State×Year* fixed effects. 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.

1.5 Examination of Pre-trends

In the end, the key assumption the TWFE relies on is the 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 light on the pre-trends:

$$\begin{aligned} \text{YTM}_{imcst} = \alpha_0 + \sum_{k=T-3}^{T-1} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum_{k=T+1}^{T+3} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k + \\ \delta_1 \text{ Controls}_{imcst} + \text{Rating}_i + \text{ Rating Agency}_i + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst} \end{aligned} \tag{3}$$

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}.

The plot of the estimates of β's in Panel (A) of Figure (IV) 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 emerged after the event. This suggests that there were no differential pre-trends in the offering yields to maturities of the bonds issued from the treated and control counties. This absence of pre-trends lends support to the causal nature of the estimates.

[Insert Figure (IV) About Here]

We further examine the pre-trends in the county-level economic variables using the following regression equation:

$$\text{Outcome}_{cst} = \alpha_0 + \sum_{k=2013}^{2014} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum_{k=2016}^{2018} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k + \alpha_{cs} + \gamma_{st} + \epsilon_{cst} \tag{4}$$

Each of the Panel (B) through (E) of Figure (IV) shows the plot of β's for the four county-level outcomes—the growth rates of employment, the number of establishments, property taxes per capita, and inter-governmental revenues per capita. The plots mostly suggest that the treated and control counties did not experience a significantly different trend in terms of these economic indicators. Overall, these analyses lend support to the parallel-trends assumption.

2 Data and Summary Statistics

We employ a range of environmental, financial, and socioeconomic datasets in our analysis. The data on PFAS contamination are from EPA's UCMR (3) program. These data contain the detection levels for the six PFAS substances in the drinking water along with the zip codes of the location of water systems. We aggregate the PFAS data to the county level using zip code crosswalk files to determine the contamination status of a county. We classify a county as contaminated if any of the zip codes within its boundaries had a water system contaminated with any of the six PFAS substances. This process yields 200 contaminated counties across 33 states. Table (II) shows key statistics on the contamination levels for the six PFAS compounds. Column (1) shows the number of counties in which a given contaminant was detected. Column (2) shows the share among the contaminated counties detected with the given PFAS. Columns (3–6) show the concentration statistics. Column (7) shows the minimum reporting level (MRL), the lowest detectable concentration under the testing technology "Method 537" employed by EPA. The table shows that 128 out of 200 contaminated counties (64%) had

PFOA contamination, with a mean detection level of 48.5 ng/L and a maximum detection of 349 ng/L, almost five times the EPA's lifetime health advisory of 70 ng/L.

[Insert Table (II) About Here]

We assemble the data on municipal bonds from 2013 till 2018 from several sources. The issuance data on municipal bonds are from Thomson Reuters Eikon. This data contain extensive information on the bond offerings, such as nine-character CUSIP, yield, coupon, amount, the zip code of issuer headquarter etc. We link the bonds to counties using zip codes of the municipalities headquarters and HUD's crosswalk of zip codes to counties. Since our identification relies on county boundaries, we exclude municipalities and bonds which cannot be assumed to operate within the boundaries of a single county.[12] After linking the municipalities to counties, we categorize those headquartered in zip codes located in contaminated counties as treated and those in bordering, uncontaminated counties within the same state as control. Considering that yields and coupons of some rare bonds are vastly different from the rest, we exclude privately-placed bonds, non-tax-exempt bonds, bonds with maturity less than a year, and bonds whose coupon is neither paid semiannually at a fixed rate nor paid exclusively at maturity. The resulting bonds constitute the sample for our analysis of primary market offering yields to maturities. It consists of 78,423 bonds (at nine character CUSIP level) issued by 2,331 municipalities from 181 counties in the treated group and 63,235 bonds issued by 1,959 municipalities from 299 counties in the control group.

Table (III) presents key statistics on new bond issues. Columns (1) through (4) show the statistics for all sample. Columns (5) and (6) show the growth rates of each variable measured separately in the treated and control counties over the pre-event time period. Column (7) shows the difference of these two columns, and Column (8) shows the p-values from the t-test for the difference. We see that a typical new municipal bond has an offering yield to maturity at issuance (primary market yield)

[12] We exclude all municipalities whose headquarters are in a zip code that spans across multiple counties. We also exclude school districts bonds, because a school district located in the 33 states in our sample spans on average across 1.6 counties. In Eikon data, these bonds can be identified with the first character of the purpose code equal to "E".

of 2.3%, coupon of 3.6%, log (maturity, in years) of 2.08, and log (amount) of 13.64. More importantly, the p-values in Column (8) are statistically insignificant, suggesting an absence of differential pre-trends across treated and control counties.

The data on secondary market transactions of municipal bonds are from Municipal Securities Rulemaking Board (MSRB). We link these to the municipal issuers and their treatment and control status using the first six characters of CUSIP. The transactions data include raw trading yield and amount for each transaction. We measure yield spread of a transaction as the difference between the raw yield of the transaction and a benchmark treasury yield.[13] We perform three screening steps. First, bonds trading less than five times a year are excluded in that year for the lack of liquidity. Second, trades within the last 12 months of a bond's maturity or the first three months of its dated data are excluded, as yields in these periods are noisy (Goldsmith-Pinkham et al., 2023; Green, Hollifield, and Schürhoff, 2007). Third, we exclude all transactions of the new bonds whose dated date falls within the sample period (2013 till 2018). The resulting transactions form our sample for analysis of the secondary market transactions. These bonds on average have a trading yield of 2.2%, trade 6.9 times per month, and the standard deviation of the dollar transaction prices calculated monthly is 0.7. The p-values reported in Column (8) show the absence of the differential pre-trends for all secondary market municipal bond transaction variables.

[Insert Table (III) About Here]

We use a host of county-level socioeconomic datasets to supplement the municipal financing data. Local government spending, property taxes, and inter-governmental transfer data are from the Annual Survey/Census of State and Local Government Finances, compiled by Pierson, Hand, and Thompson (2015). Public sector employment data are from the Annual Survey of Public Employment & Payroll (ASPEP). Homeownership and migration data are constructed from the Statistics of Income (SOI) pro-

[13] Benchmark treasury yield is the maturity-weighted average of the same-date yields on a combination of treasury bonds of maturities just lower and just higher than the remaining maturity of the municipal bond. Consider a transaction of a municipal bond with remaining maturity of 31 months. Since treasury with maturity of 31 months do not exist, we select the two closest treasury bonds, 24-month (y_{24}) and 36-month (y_{36}) on the date of the transaction and define the benchmark yield as $(5/12 \times y_{24} + 7/12 \times y_{36})$.

vided by Inland Revenue Service. The data on establishments and employment come from Census Bureau's County Business Patterns data. We construct county-level measure of PFAS-related industries using data from EPA's Toxic Release Inventory (TRI) program for the years 2020 and 2021, the first two years since these data have been collected in the U.S. Finally, we measure county-level quality of drinking water infrastructure as the total number of health-related violations of the federal U.S. Safe Drinking Water Act reported under Safe Drinking Water Information System. We use county FIPS to link all these datasets together. The p-values in Column (8) for the test of difference in the growth rate of the variables in pre-event time period across the treated and control are statistically insignificant.

Our analysis of municipal bonds holding centers on holdings by mutual funds and banks. The data on holdings by mutual fund come from Center for Research in Security Prices (CRSP) mutual fund database which we link to the municipal bonds using the 6-character CUSIP. Also, data on bank holding come from Call Reports and Summary of Deposits and are linked to the counties using county FIPS. Section (3.2.A) and Section(3.2.B) provide detailed linking procedure and the construction of the variables we use in the analysis.

3 Results

3.1 Contamination Discovery and Offering Yields to Maturity

We begin the empirical analysis with evaluating how the offering yields to maturity changed after the event. Specifically, we use the following regression:

$$\text{YTM}_{imcst} = \alpha_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} + \delta_2 \text{ County Controls}_{cst} + \text{Rating}_i + \text{Rating Agency}_i + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst}\,, \quad (5)$$

where YTM_imcst is the offering yield to maturity 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.[14] $Bond\ Controls_{imcst}$ include bond amount (in log), bond tenure in years (in log), inverse of log bond tenure (in year), and indicators for whether the bond is callable, insured, and whether the offering type is competitive or negotiated. $County\ Controls_{cst}$ include six variables at the county level. Four of these controls are the annual growth rates of employment per 1000 population, the number of establishments, property taxes per capita, and inter-governmental revenue per capita. The remaining two are the ratio of the number of establishments in the PFAS-emitting industries to the total number of establishments and the per capita number of health-related drinking water code violations. $Rating_i$ denotes bond rating fixed effects.[15] α_{cs} denotes county fixed effects, γ_{st} denotes $State \times Year$ fixed effects, and Capital-type_i denotes capital-type fixed effects.

[Insert Table (IV) about here]

Table (IV) 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 8–9 basis points (bps) in offering yields to maturity relative to a municipality from a neighboring uncontaminated county after the discovery of the contamination. The estimate in Column (1) is obtained with only bond-level covariates and in Column (2) with bond- and county-level covariates. Our preferred estimate is the latter, suggesting that the offering yields to maturity of new bonds issued by the affected municipalities increased on average by 9 basis points.

Recall that one of the assumptions of our empirical approach is that the contamination occurred in the past and the locations were not easily predictable. We argue that these are more likely to hold for PFOA and PFOS, because these two chemicals had been manufactured the longest, used the most, and had been phased out in the U.S.

[14] Since the event occurred mid-year, August 9, 2016, it does not align with calendar year fixed effects in an annual panel, creating issue for TWFE specification. Hence we created synthetic year based on 365-day interval counting from the event date and use it for year fixed effects.

[15] Rating takes the value of 1 for Aaa rating, 2 for Aa1, ... and, 10 for Baa3. All the unrated bonds and about 0.1% of lower-rated bonds are together assigned a separate category.

since around 2008. Thus we repeat the above regressions for the sample of counties contaminated with these two chemicals and the bordering counties uncontaminated by any of the six PFAS. Columns (3) and (4) show that the estimates of increase in yields after the contamination discovery remain similar.

These estimates are robust to any time-invariant differences across counties (owing to county fixed effects), any annual changes at the state level such as gubernatorial elections or fiscal policies (owing to *State*×*Year* fixed effects), changes in ratings (owing to rating category fixed effects), or contemporaneous nationwide changes such as policy interest rates (owing to the DD estimation).

To understand the economic magnitude of this rise in yields, we note that it is more than the increase in yields caused by a decline of two notches in rating on Moody's rating scale from the highest category Aaa to Aa2 (6 bps). Alternatively, this increase in the yields is equivalent to a 4.5% rise over the average yields of the bonds issued by affected municipalities in the pre-event year. In terms of interest payment, the rise in yields resulted in increased annual payments by $102.28 million. The magnitude of the increase in the offering yields is also similar to that caused by some of the other factors documented in the municipal finance literature (K. R. Cornaggia et al., 2021; Gao et al., 2020; W. Li and Zhu, 2019; Painter, 2020; Chava et al., 2023; Gao, Lee, and Murphy, 2019; Goldsmith-Pinkham et al., 2023).

We hypothesize that the increase in offering yields reflects bond market's view on increased default risk of municipalities contributed by two factors. First, the contamination discovery results in an unexpected increase in expenditure for municipalities for clean up and abatement. For an anecdotal example of this, see Footnote (6). Second, the contamination event depresses expected future revenues of municipalities from worsening out-migration, employment, and municipal expenditure. The worsening effect is compounded by the fiscal multiplier effect (Dagostino, 2018; Adelino et al., 2017). Since municipalities are expected to balance their operating budgets and their long-term borrowing often requires voter approval (Ang et al., 2017; Haughwout et al., 2021), their default risk rises.

To examine the mechanism, we begin with analyzing whether the rise in yields reflects default risk. We conduct a series of cross-sectional tests dividing the estimation sample according to the characteristics commonly argued by the municipal finance literature to be associated with default risk (K. R. Cornaggia et al., 2021; K. Cornaggia et al., 2022; Gao et al., 2020). We utilize a triple difference (DDD) estimator of the following general form:

$$\begin{aligned}\text{YTM}_{imcst} = \beta_0 \,+\, \boldsymbol{\beta_1}\ \text{Treatment}_{cs} \times \text{Post}_t \times \mathbb{X} + \beta_2\ \text{Treatment}_{cs} \times \text{Post}_t \,+ \\ \beta_3\ \text{Treatment}_{cs} \times \mathbb{X} \,+\, \beta_4\ \text{Post}_t \times \mathbb{X} \,+\, \beta_5 \mathbb{X} + \,+ \delta_1\ \text{Bond Controls}_{imcst} \,+ \\ \delta_2\ \text{County Controls}_{cst} + \text{Rating}_i + \text{Rating Agency}_i + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst}\ .\end{aligned} \tag{6}$$

In this DDD specification, $\mathbb{X}$ is a dichotomous variable representing a characteristic that will be used as the third-difference. The general idea is that the offering yields to maturities in the primary market will see a larger increase for the characteristics associated with a higher risk. The coefficient β_1 captures this effect. We use five dichotomous characteristics for the third difference: type of cash-flows backing the bond repayments, bond maturity, dependence of counties on inter-governmental transfers for revenues, homeownership rate, and availability of state fiscal support for distressed municipalities.

Our first measure is based on the source of the cash-flows that back the bond repayments. General obligation (G.O.) municipal bonds are backed by the taxation power of the municipalities and carry lower default risk than other bonds. Thus the effect of the event should be less pronounced for G.O. bonds than for other bonds. Consistent with this prediction, the estimate in Column (1) of Table (V) shows that the increase in the offering yields of treated G.O. bonds was smaller by 7 bps than the treated non-G.O. bonds, while adjusting for any trends in the bordering uncontaminated counties.

[Insert Table (V) Here]

The second risk characteristic is bond maturity. Longer maturity bonds are considered riskier than otherwise similar shorter maturity bonds (Painter, 2020). If the contamination discovery raises the default risk of the bonds, the increase in yields would be larger for the longer maturity bonds. We classify the bonds with maturity larger than 15 years as long term and the others as short term. The coefficient in Column (2) suggests that the bonds of longer maturity experienced a 7 bps larger increase than those of shorter maturity after the event.

The third risk characteristic is based on fiscal dependence of counties on revenues from intergovernmental transfers. The counties for whom such transfers form a larger share of revenues are expected to experience larger rise in default risk and thus experience higher increase in yields (Chava et al., 2023; Cheng, De Franco, and Lin, 2023; Gao, Lee, and Murphy, 2022; Hasan, Krause, and Qi, 2020). Using government finance data from Pierson et al. (2015), we calculate the ratio of intergovernmental revenues to total revenues for all county-level governments in the pre-event year 2015. We then assign the counties whose ratio was greater than the cross-sectional median to the high-dependence group and the others to the low-dependence group. Column (3) of Table (V) shows the result of the regression. Municipalities from the affected high-dependence group suffered a larger increase in offering yields of 11 bps than the affected counties in the low-dependence group. The estimate is similar and significant when we use the cross-sectional mean, instead of median, to classify the counties and is unreported for brevity.

The fourth characteristic we analyze is a non-pecuniary measure highlighted by K. R. Cornaggia et al. (2021). They argue that community ties of the residents are a determinant of the capital supply available to the local governments, because homeowners and property-owners have more interest in their local community and have higher willingness to provide capital to meet any unexpected heightened local borrowing needs. We use IRS SOI data and define county-level homeownership rate as the ratio of the number of income tax filings with mortgage items to the total number of filings. Then we use the cross-sectional median of this ratio across the sample counties in the pre-event year 2015 to classify counties into high and low home-ownership groups. We use this classification in the DDD specification from Equation (6). The coefficient in Column (4) suggests that the affected counties with low homeownership rate experienced a higher increase of 11 bps in offering yield to maturities relative to the affected counties with low-home-ownership rates. The estimate is similar and significant when we use the cross-sectional mean, instead of median, to classify the counties and is unreported for brevity.

The fifth risk characteristic we utilize is based on the support policy of a state regarding distressed municipalities. Gao et al. (2019) classify nine states in the U.S. as having proactive policies to assist distressed municipalities (ME, MI, NC, NJ, NY, OH, PA, NV, and RI) and argue that these policies minimize the risk of default of municipalities from these states relative to those from other states. Thus we predict that the municipalities in non-proactive states (all states other than proactive states) will see a higher increase in the offering yields to maturities after the contamination discovery than those from the proactive states. Consistent with the prediction, the estimate in Column (5) suggests that the offering yields of affected municipalities in non-proactive states rose on average 6 bps more than the affected municipalities in the proactive states.

To summarize, our findings from triple difference specifications suggest that the yields increased more for bonds containing the five commonly used dichotomous risk characteristics.

3.2 Rising Offering Yields and Supply of Capital

Having established that the offering yields to maturities increased after the contamination discovery in a manner consistent with default risk, we next examine the link between the rise and a reduction in supply of capital by mutual funds and banks, two important investors in the municipal market. It has been shown that institutional demand for bonds and the differences in their investment mandates can affect the pricing of the corporate bonds (Bretscher et al., 2022). In the case of municipal bonds, mutual funds and banks have been shown to affect their pricing (Bergstresser and Orr, 2014;

Ivanov and Zimmermann, 2019; Y. Li et al., 2023; Yi, 2020). Thus we investigate next changes in supply of capital by mutual funds and banks to the affected municipalities. Since these investors are considered sophisticated, their decisions are more likely to be driven by changes in fundamental characteristics of municipalities, such as default risk, than by sentiments.

3.2.A Mutual Funds' Allocation to Affected Municipalities

Mutual funds are the second-largest investor in the municipal bond market, holding about 30% of the total outstanding municipal bonds (Y. Li et al., 2023). More importantly, they invest early in the new municipal bonds and gradually sell their stakes to other investors (Azarmsa, 2021), indicating that they play more active role in pricing of new bonds than already-issued bonds. We examine the changes in allocation of mutual funds to the affected municipalities following the same DD framework.

We identify all the municipal issuers in our sample using the 6-character CUSIP related to all the new bond issues from sample counties from 2013 to 2018. We then merge these 6-character CUSIPs with the bond holding data of all mutual funds in the CRSP Mutual Fund database. All 6-character CUSIPs of the bonds issued by municipalities from the affected counties are classified as *Treated* and those from the surrounding same-state uncontaminated counties as *Control*. We regress the mutual fund holdings allocated to bond i by a fund f in year-quarter q using the following equation on the panel data defined at *fund×CUSIP8×year-quarter* level:

$$\text{Y}_{ifq} = \beta_0 + \beta_1 \text{ Affected Bond}_i \times \text{Post}_q + \gamma \text{ Controls} + \alpha_i + \delta_f + \lambda_q + \epsilon_{ifq} \tag{7}$$

The regression specification includes bond (eight-character CUSIP), fund, and year-quarter fixed effects. Controls include management fees, expense ratio, and natural log of one-quarter lagged values of fund's total net assets and underlying bond's market value. Table (VI) presents the results from the regression. The result for funds' allocation (in bps) to bonds in Column (1) suggests that mutual funds reduced their allocation to the affected municipalities by 0.34 bps relative to the unaffected ones. This represents a decline of 2.3% from the pre-event median allocation of 15 bps to an affected bond. This decline does not necessarily represent a reduction in allocation and supply of capital to the affected municipalities. If allocation by funds is proportional to the market value of underlying bonds, then an increase in the yields of the affected bonds would mechanically reduce the allocation (market value benchmarking). To distinguish if our estimate is driven by such automatic reduction of allocation or by active reduction in the bond holdings of the funds, we next regress the log of the number of bonds held by the funds using the same specification. The estimate reported in Column (2) suggests that funds reduced the number of affected bonds by 1.2 percentage points. This corroborates the interpretation that funds reduced capital supply to the affected municipalities. Moreover, the reduction was significant only for active mutual funds (Columns 3 and 4), but not for index funds (Columns 5 and 6). This difference across the two types of funds further reaffirms our interpretation that these declines were not merely a result of market value benchmarking. Taken together, we conclude that active mutual funds reduced supply of capital to the affected municipalities after the contamination discovery.

[Insert Table (VI) about here]

3.2.B Banks' Holdings of Municipal Bonds and Loans

Drawing from the conclusions in Ivanov and Zimmermann (2019) and Yi (2020) that municipal bond holdings by banks also affect municipal finances, we set out to examine changes in banks' holdings after the contamination discovery. We note a challenge with this analysis: the bond-level holdings of banks are not publicly observable. We thus focus on aggregate bank-level changes in municipal holdings of those banks whose deposit activity is concentrated in affected counties versus control counties. We assign the banks having deposits concentrated across the treated counties in the pre-event period to treatment group and those having deposits concentrated in the control counties to control group.[16] We use the following DD regression equation on a panel data defined

[16] We begin with the Summary of Deposit data of the banks and find all such banks whose total deposits (annual domestic deposit) in the sample counties constitute more than 50% of their total deposits across

at the *bank*×*quarter* level:

$$\text{Bank's Municipal Holdings}_{bq} = \beta_0 + \beta_1 \text{ Treatment}_b \times \text{Post}_q + \delta_1 \text{ Controls}_{bq} + \alpha_b + \gamma_q + \epsilon_{bq} \tag{8}$$

Here *Bank's Municipal Holdings*$_{bq}$ is bank b's holding of either municipal bonds or loans in quarter q, scaled by its total assets. The holding of municipal bonds is measured in two ways: as the ratio of held-to-maturity municipal bonds under the fair value method (RCFD8497) to bank's total assets, and as the ratio of held-to-maturity municipal bonds under the amortized cost method (RCFD8496) to bank's total assets. Bank's loan to municipalities is measured as the ratio of municipal loans (RCFD2107) to bank's total assets (RCFD2170). *Controls* include net interest margin, return on assets, and the growth rate of total assets.

[Insert Table (VII) about here]

Table (VII) presents the results. The estimates in Columns (1) and (2) suggest that banks whose deposits were concentrated in the affected counties reduced their holdings of held-to-maturity municipal bonds—at fair value or at amortized cost—by about 20 basis points. The reduction in Column (2) indicates an active reduction in supply of capital by the treated banks to the affected municipalities, not a mere decline in the value of the bonds.[17] The result in Column (3) indicates no decline in municipal loans. This is likely because loan contracts are usually multi-year contracts and cannot be disposed of as easily as bonds.

Overall, we conclude that the reasons the offering yields of the affected municipalities increased include a decrease in supply of capital from mutual funds and banks,

the U.S. over the pre-event years (2013–2015). For each such banks, we calculate mean of the annual deposits over the pre-event years for treated and control counties. We then calculate the share of deposits in the treated counties as the ratio of the mean deposit in treated counties to the mean deposit in the sample counties. A bank is then classified as treated if its share in treated area is higher than the cross-sectional mean of the share across banks.

[17] A decline in bank's holding of municipal bonds under Fair Value method could result from a mechanical decline in the market value of the bonds when their yields rise. However, a decline in value of holdings under amortized cost method does not depend on market value of the underlying bonds (Marsh and Laliberte, 2023, P.3), hence a decline under this method reflects an actual reduction in the number of bonds held, not just the changes in the market value of the existing holdings.

two important institutional municipal investors. Also, since these are sophisticated investors compared to households, their allocation decisions are less likely to be driven by sentiments and more by changes in fundamental characteristics of municipalities.

3.3 Out-migration as a Source of Economic Stress

A large proportion of municipal revenues comes from the areas in which they operate, hence out-migration can shrink their taxable economic base and affect their default risk (Hastie, 1972; J. Cornaggia et al., 2019; Yi, 2020). We thus examine changes in out-migration in the affected areas after the contamination discovery as a potential source of economic stress for the municipalities. Utilizing the county-to-county migration data from the IRS SOI dataset, we examine the patterns in out-migration and income levels of out-migrating population from the affected counties after the event. These outcome variables are estimated using the following DD equation on a panel dataset defined at the *county×year* level:

$$Y_{cst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \text{ County Controls}_{cst} + \alpha_{cs} + \gamma_{st} + \epsilon_{cst} \,, \tag{9}$$

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. County controls include the share of PFAS industries, quality of water infrastructure, and the annual growth rates of employment per 1000 population, the number of establishments, property taxes per capita, and inter-governmental revenue per capita.

[Insert Table (VIII) about here]

The first outcome variable is "within state net out-migration". It is the outflow from a focal county to other same-state counties minus the inflow from all other same-state counties to the focal county, scaled by the population of the focal county. Column (1) of Table (VIII) suggests 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 net out-migration flow from the treated counties in the pre-event period was −0.09%.

In Columns (2) through (4), we examine whether it's the high or low income population who is out-migrating. The dependent variable in Column (2) is the Adjusted Gross Income (AGI) of the out-migrating population minus that of the in-migrating population, scaled by AGI of out-migrants. In Column (3), the dependent variable is the AGI of in-migrating population minus the AGI of residents, scaled by AGI of residents. In Column (4), the dependent variable is the AGI of out-migrating population minus the AGI of residents, scaled by AGI of residents. The estimate in Column (2) suggests that the out-migrating population had 2.66 percentage points higher income than in-migrating population. The estimate in Column (3) suggests that in-migrating population had 0.18 percentage points lower income than the resident population. Finally, the estimate in Column (4) indicates that the out-migrating population had similar income to that of residents.

We conclude that the contamination discovery increased out-migration from the affected counties to other counties of the state and also resulted in the inflow of lower income residents.

3.4 Response of the Affected Municipalities

Our results so far suggest that the contamination discovery resulted in higher bond yields, reduced supply of capital, and increased flight of high-income population. It is natural to expect that municipalities would respond by undertaking expenditure-saving measures. We thus investigate public (municipal) expenditure and public sector employment next. We aggregate total public expenditure to the county-year level for all county and smaller municipal governments.[18] The regression specification and controls are from Equation (9), and results are shown in Table (IX).

[18] Definition of expenditure is from Pierson et al. (2015). Specifically, total expenditures are the sum of direct expenditures and intergovernmental expenditures. Direct expenditures can further be broken down into 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. Capital outlay expenditures are the sum of construction and purchase expenditures.

[Insert Table (IX) about here]

Columns (1), (2) and (3) indicate that relative to the control counties, the affected counties experienced a significant decline in public expenditure. Total, general, and direct general public expenditure declined by $125, 103, and 94 per capita, respectively. Total expenditure declined by 3.1% from its average level in the affected counties in the pre-event period. Employment in the public sector also experienced reductions. The estimates in Columns (4) and (5) show that full-time-equivalent public employment per 1000 population shrunk by about 2.2 and the share of public employment in total employment declined by 1 percentage point. In economic terms, the decline in public employment is equivalent to about 9% decline from the average public employment in the affected counties in the pre-event period. These magnitudes are non-trivial and are similar to those found in Amornsiripanitch (2022) and Chordia et al. (2022). Furthermore, since local governmental spending has a fiscal multiplier effect (Adelino et al., 2017; Dagostino, 2018), these reductions compound the adverse effect, even though they are consistent with expenditure-minimization.

All in all, we find that the contamination discovery resulted in worsening real economic outcomes. These deteriorations in real outcomes also indicate that the reduction in supply of capital by mutual funds and banks was likely a rational decision.

4 Supplementary Discussion

In this section, we discuss supplementary results that aid in interpreting previous results and also help in ruling out some alternative explanations.

4.1 Effect on Municipal Bond Issuing Activities

So far we have estimated the effects of contamination discovery on the offering yields to maturities of the new municipal bonds issued in the primary market. These findings are contingent upon municipalities opting to issue these new bonds. The observed increase in yields after the event potentially incentivizes the affected municipalities to defer bond issuance to a later period. Consequently, our results are driven by those municipalities that were unable to postpone their bond-raising activities. To understand whether such postponement occurred, we plot the fraction of the treated (and control) municipalities issuing bonds in any given year in Figure (V). The plot reveals that there was no significant drop in the fraction of municipalities issuing bonds. This is also in line with the idea that municipalities issue bonds fairly regularly.

[Insert Figure (V) about here]

Keeping in mind that the contamination discovery would require infrastructure expense, and more so in the short-term, we next investigate the county-aggregated amount across all bond maturities and the county-aggregated ratio of annual issuance amount raised for short term (maturity ≥10 years) to those raised for long term (≥10 years). The specification is from Equation (9) and Table (X) shows the results.

[Insert Table (X) about here]

The estimate in Column (1) suggests that there was no discernible increase in the total amount borrowed by affected counties. Meanwhile, the estimate in Column (2) suggests that, relative to the unaffected municipalities, the affected municipalities increased the ratio of short-term borrowing to long-term borrowing by 0.53. We thus conclude that following the contamination discovery, municipalities tilted their bond issuance activities towards shorter-term borrowing, consistent with the heightened needs for investments in water infrastructure.

4.2 Legal Liabilities as a Source of Economic Stress

Previously we documented a deterioration in economic outcomes after the contamination discovery: heightened net out-migration coupled with the in-migration of lower income population and reduced per capita public expenditure and employment. In addition, we highlight the growing legal liabilities as another potential factor affecting the municipal issuers and local governments, though we do not attempt to quantify it. After the contamination discovery in 2016, lawsuits have been filed against city, water utilities, and county. For example, Tennessee Riverkeeper Inc. filed a federal lawsuit against BFI Waste Systems (a municipality in the city of Decatur, Alabama), against City of Decatur Alabama, against Morgan County, and against 3M for the dumping of PFOS and PFOA chemicals in Tennessee River and landfills under Resource Conservation and Recovery Act of 1976 (The Decatur Daily (Alabama), June 25, 2016). We note that Morgan county is one of the contaminated counties in our sample. At the same time, numerous lawsuits and multidistrict litigation are brought up jointly by several water systems, state attorneys, and local governments from across the U.S. against the PFAS manufacturers. As noted in Footnote (2), there are more than 15,000 active PFAS-related claims ongoing, including multidistrict litigation by water utilities and state attorneys. For example, Cape Fear Public Utility Authority and Brunswick County filed lawsuits against E.I. Du Pont De Nemours and Company, the Chemours Company, and Dow Dupont Inc. (Court Listener, Oct. 16, 2017). We again note that Brunswick County is one of the affected counties in our sample.

4.3 Effect of Contamination Intensity

The UCMR (3) program revealed not only whether a county's drinking water system was laced with PFAS, but also the extent of the contamination. So one may anticipate that the areas with higher contamination levels would experience a greater increase in the offering yields. However, this prediction assumes that the costs associated with cleaning the contamination and installing the necessary technology and infrastructure to prevent future contamination are proportional to contamination levels. However, as previously noted in Footnote (5), such technology was largely unavailable at the time of the event, and the necessary infrastructure upgrade required substantial fixed costs. Consequently, it remains unclear whether the increase in the yields will indeed vary with the concentration levels of the contaminants. Our analysis does not detect a statistically significant difference in the increase in yields across counties with higher contamination levels or a greater number of PFAS contaminants.

4.4 Why Did the Effect on Offering Yields Not Persist for Longer?

We note from Panel (A) of Figure (IV) that the increase in the offering yields of the municipal bonds from the contaminated counties remained pronounced for about three years before gradually diminishing. One may naturally question: if the contamination event indeed imposed financial constraints on municipalities, why did the heightened yields not persist for a longer duration? Was the rise temporary because the underlying reason was heightened sentiments? We note that behavioral explanation such as sentiment is not consistent with several of our findings. First, several real outcomes worsened after the event, e.g., out-migration, employment, expenditure. Second, institutional investors—who are considered sophisticated and are less likely than households to be driven by sentiments—reduced allocation in the bonds of the affected issuers by after the event. Third, several anecdotal examples mention contamination as the reason for budgetary provisions, legal cases, and municipal bond raising activities related to clean up. We conjecture that the reason the effect did not persist over a longer period is the heightened attention from regulators and legislators at both state and federal levels aimed at mitigating the issue and providing fiscal support.[19] Notably, the 116th Congress introduced over 80 pieces of legislation concerning this matter (National Conference of State Legislatures, Jan 25, 2021) and discussions of a federal regulation on PFAS concentration in drinking water are ongoing (Federal Register, EPA, Mar 10, 2020). At local level, numerous regulatory initiatives have been proposed, with some successfully enacted (PFAS Project Lab, 2023b).

[19] Budgetary provisions for cleaning up the contamination and testing the local population for adverse effects were made by several states after the discovery. For example, 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 set aside funds for PFAS 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 (S.B. 176, 2020). Moreover, several states considered costs of infrastructure upgrade. California appropriated $30, 50, and 90 million to address PFAS in drinking water systems in the budget act of 2021, 2022, and 2023 (SB170, SB154, and SB101). Wisconsin transferred $ 110 million and $ 15 million to the state's PFAS fund from its general fund and environmental management fund in 2023 (SB70). Michigan allocated $34.7, 23.5, and 39 million for PFAS remediation (SB0082, HB5783, and HB4437). Maine in 2021 provided $29.5 million (LD221/HP156) and Florida in 2023 provided $29.6 million (HB5001) for PFAS mitigation.

4.5 Effect on Yields of Already-issued Bonds

Our analysis is primarily focused on analyzing offering yields to maturities of new municipal bonds, which represent the realized borrowing costs for the issuers, because they are primary market yields. Analyzing trading yields in the secondary market of the already-issued bonds can further corroborate views of the investors on the municipal default risk. Analyzing the trading yields also allows us to observe the changes in investors' views on the same bond over time. We use the following regression equation to identify within-bond changes in secondary market yields of municipal bonds:

$$\begin{aligned} \text{Y}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst} \\ + \delta_2 \text{ County Controls}_{cst} + \alpha_{imcs} + \gamma_{st} + \epsilon_{imcst} \end{aligned} \tag{10}$$

where Y_{imcst} is either the raw trading yields or the spread on the trading yields. Raw trading yield of a bond i is the monthly volume-weighted average of raw trading yields (in percentages). Similarly, trading yield spread is the monthly volume-weighted average of the yield spread of individual trades, where yield spread is the difference between the raw trading yield and a benchmark yield estimated from treasury yields. The detailed steps to calculate benchmark yield are noted in Footnote (13). 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_{st}. *County Controls*$_{cst}$ are the same as in Equation (5). *Bond Controls*$_{imcst}$ include log of the remaining maturity (in years) on the transaction day, and inverse of the remaining maturity (in years) on the transaction day, monthly standard deviation of the bond's dollar transaction prices, and the number of trades in the transaction month.

[Insert Table (XI) about here]

Table (XI) reports the results. The coefficients in Columns (1) and (2) suggest that both the trading yields and trading yield spreads on the bonds issued by municipalities from contaminated counties increased by about 1.6 bps relative to the bonds issued by municipalities from bordering uncontaminated counties. In essence, the patterns in the secondary market trading yields reaffirm the conclusions we drew from the analysis of the primary market offering yields to maturities.

5 Conclusion

In this paper we show that the discovery of contamination by unregulated and unmonitored contaminants results in adverse consequences for the affected areas through the municipal bond markets. Using a difference-in-differences approach, we show that the sudden revelation in 2016 that the drinking waters of 200 counties in the U.S. was contaminated with the per- and polyfluoroalkyl substances (PFAS) resulted in an increase in offering yields to maturities (primary markets yields) of the municipal bonds issued by the municipalities from these contaminated counties by 9 basis points relative to the bonds issued by municipalities from the bordering uncontaminated counties from the same state. We find that the increase was greater for the riskier bonds, and a reduction in the supply of capital by the mutual funds and banks explains the increase. After the event, out-migration from the contaminated counties increased and municipalities responded by reducing the expenditure and public employment. These deteriorating economic outcomes rationalize the reduction in capital allocation by the investors, and suggest that these findings are not driven by sentiments. As legislative discussions regarding regulating these chemicals and implementing detection limits continue to evolve in the U.S.at both the federal and state levels (PFAS Project Lab, 2023b), as well as in other countries (WQA, n.d.), these findings carry implications of broader interest.

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Figure I: The Event

Panel A of this figure shows the publication of the findings of Hu et al. (2016) in the Harvard Gazette (The Harvard Gazette, Aug 9, 2016). Panel B shows the Google Search Interest for the term "PFAS" originating from the U.S. over 2015 to 2017 period.

Panel A: The Harvard Gazette Article

Panel B: Google Search Interest for the Keyword "PFAS"

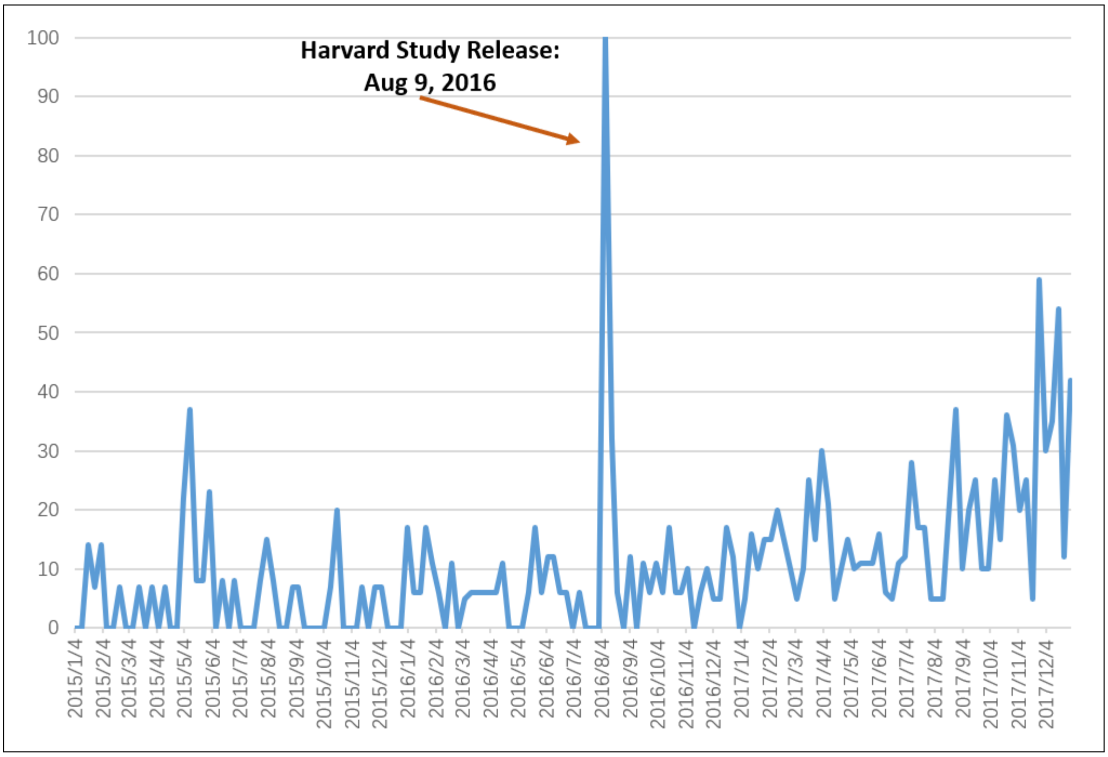


Figure II: Illustration of Treatment and Control Counties

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

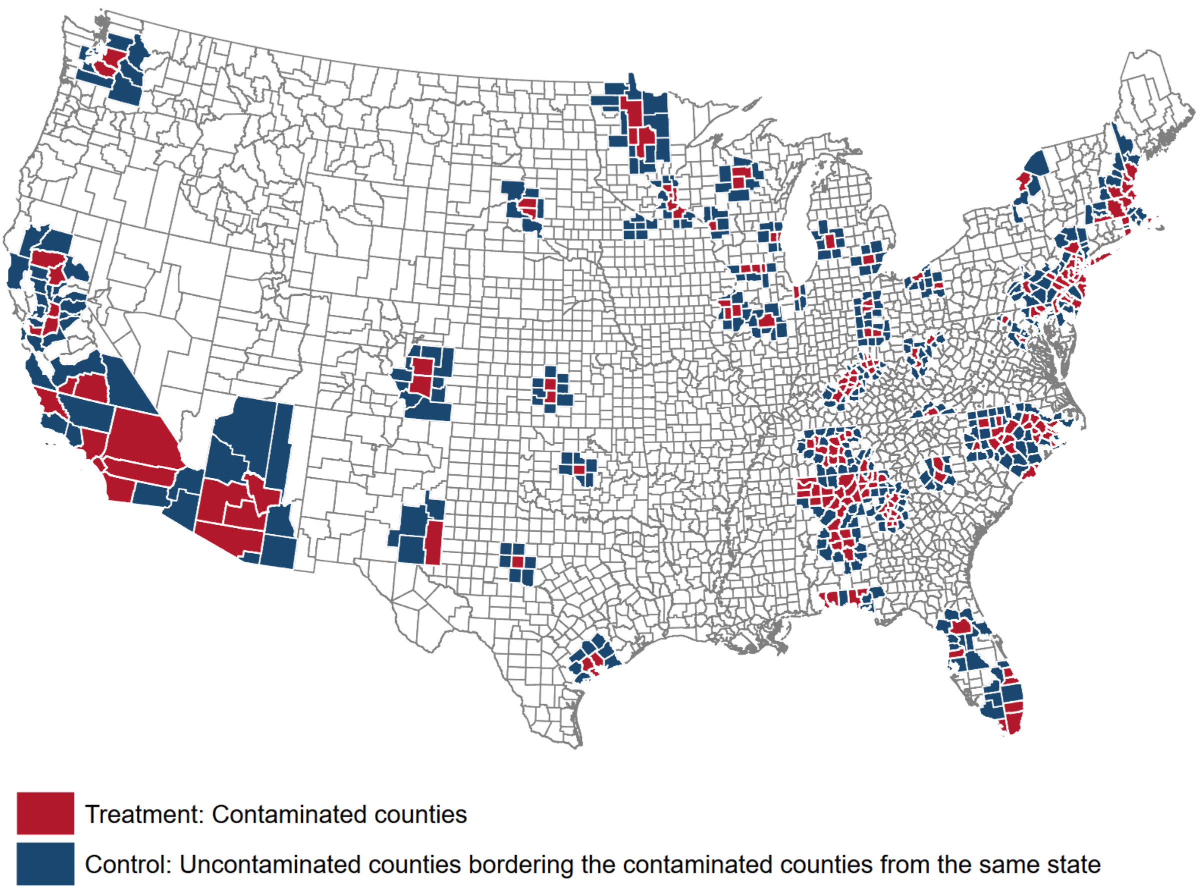
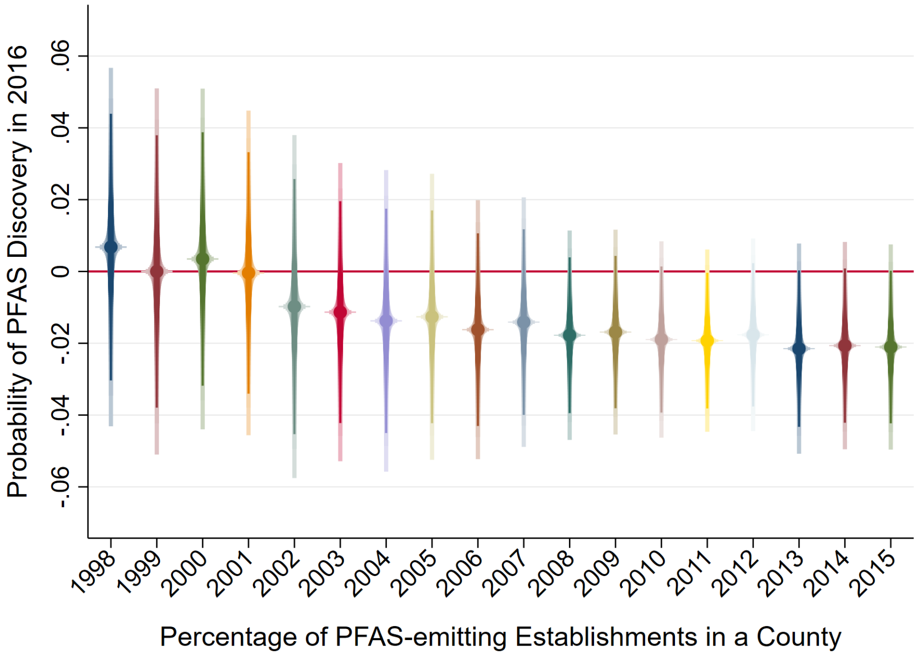


Figure III: Predicting the 2016 Discovery of PFAS Contamination of Drinking Water

Panel (A) of this figure shows the coefficients obtained from regressing the dummy variable Treatment on the percentage of establishments in a county in PFAS-releasing industries. Panel (B) shows the coefficients obtained from regressing the dummy variable Treatment on per capita violations of health-based code of drinking water in a county from 1998 till 2015. Dark-colored spikes mark the 95% confidence interval, and the light-colored spikes mark the 99% confidence intervals.

Panel A: Effect of Share of PFAS-releasing Industries on PFAS Discovery



Panel B: Effect of Health-based Drinking Water Violations on PFAS Discovery

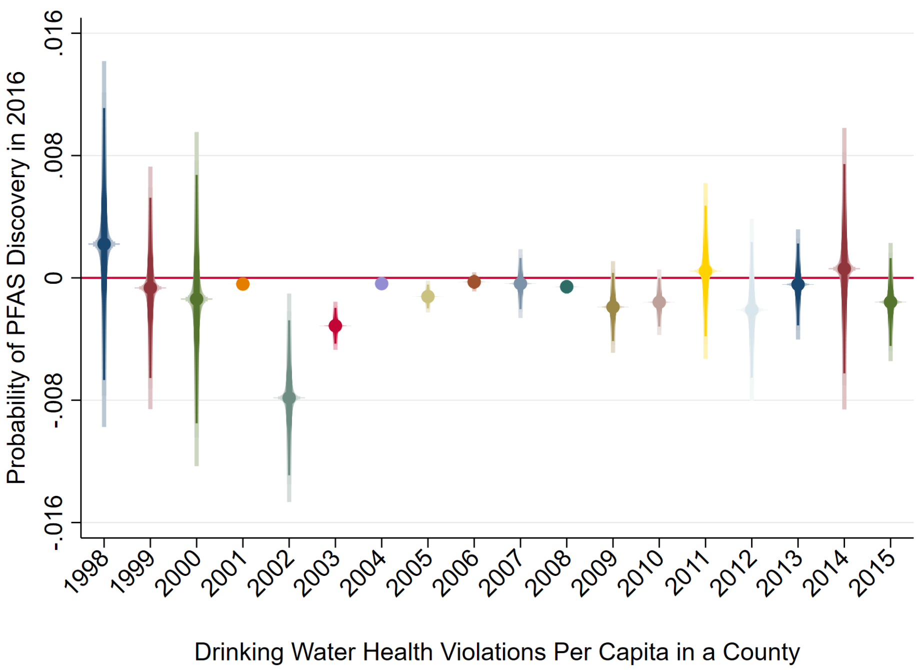


Figure IV: Parallel Trends

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

$$\text{YTM}_{imcst} = \alpha_0 + \sum\nolimits_{k=T-3}^{T-1} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum\nolimits_{k=T+1}^{T+3} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k + \delta_1 \text{ Controls}_{imcst} + \text{Rating}_i + \text{ Rating Agency}_i + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst}$$

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 four *County*×*Year*-level outcomes—growth rate of employment, number of establishments, property taxes per capita, and intergovernmental revenues per capita using the regression equation:
$\text{Outcome}_{cst} = \alpha_0 + \sum_{k=2013}^{2014} \beta_k \text{Treatment}_{cs} \times \text{Year}_k + \sum_{k=2016}^{2018} \beta_k \text{ Treatment}_{cs} \times \text{Year}_k + \alpha_{cs} + \gamma_{st} + \epsilon_{cst}$

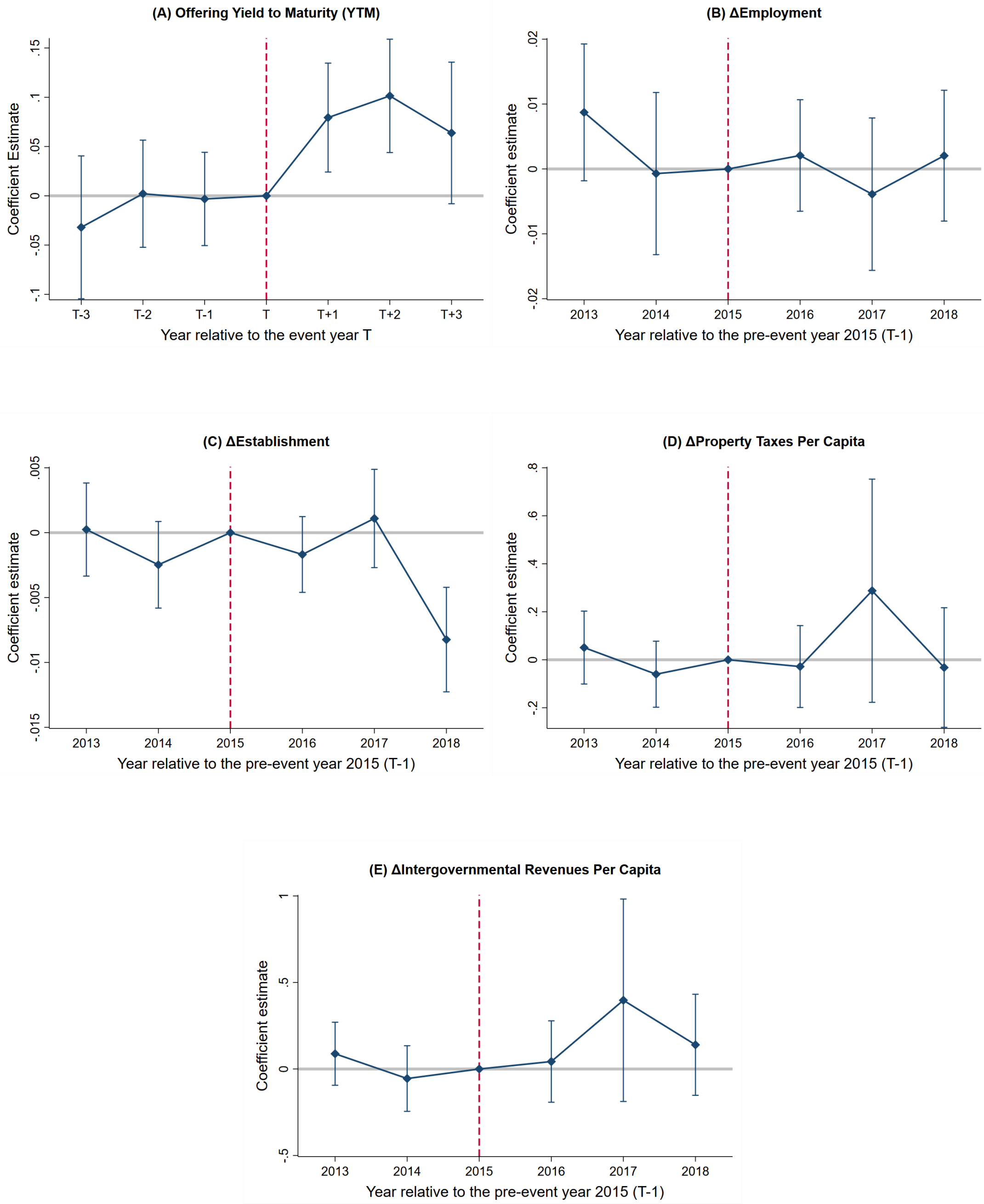


Figure V: Share of Municipalities Issuing Bonds Over the Years

This figure shows the fraction of the total municipalities in treated and control counties respectively issuing bonds in a given year.

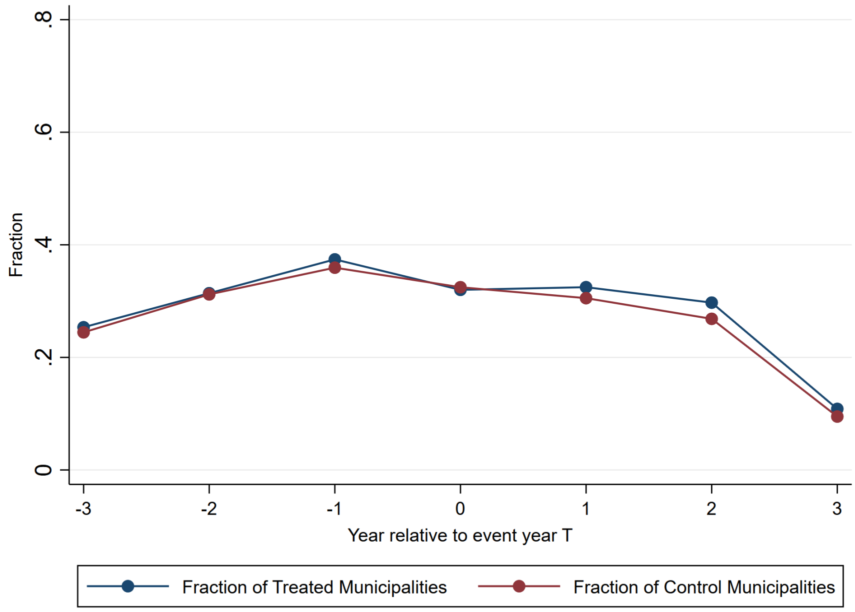


Table I: Major Developments Surrounding PFAS in the U.S.

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), PFAS Project Lab (2023a) 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: For the first time, a non-enforceable Lifetime Health Advisory limit on PFAS was set at 70 ppt by the EPA (EPA, 2016).
	◦ 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 for Contamination-related Variables

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.

	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 III: Summary Statistics for Municipal Bonds and County Characteristics

Columns (1) through (4) of this table show statistics for the full sample. Column (5) and (6) show the growth rate of the variable in treated and control counties respectively over the pre-event time period. Column (7) shows the difference between the growth rates and Column (8) shows the p-value from the t-test of whether the difference is 0. *YTM* denotes offering yield, which is the yield to maturity at issuance (in percentages). *Coupon* is in percentages. *Ln* (*Issue Amt.*) is the natural log of dollar amount issued. *Ln* (*Tenure in years*) is the natural log of the bond tenure measured in years. *Ln* $(\textit{Tenure in years})^{-1}$ is the inverse of the Ln(Tenure in years). *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. *Insured* is a dummy variable taking the value of 1 if the bond is insured and 0 otherwise. *Semiannual* is a dummy variable taking the value of 1 if the bond pays coupon semi-annually and 0 otherwise. *Trading Yield* is calculated at the month level volume-weighted average of the raw trading yields (in percentages) for each bond. *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. *PFAS Industry Share* is the share of the establishments in PFAS-emitting 3-digit NAICS industries in a county. *Water Code Violations* is the county-year health violations in drinking water. Δ *Prop. Taxes Per Capita*, Δ *IGR Per Capita*, Δ *Num. Employment*, and Δ *Num. Estab.* are the annual growth rates of per capita property taxes, inter-governmental revenues per capita, the number of employment per 1000 adults, and total number of establishments respectively.

	Full Sample				Difference in growth rate across treated and control counties over the pre-event period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	Mean	Median	SD	ΔVar_{treat}	$\Delta Var_{control}$	(5-6)	p-val (5-6)
YTM(%)	140392	2.331	2.300	0.996	0.006	0.015	-0.009	0.657
Ln(Issue Amt.)	140330	13.645	13.430	1.556	0.009	0.012	-0.003	0.423
Coupon(%)	141612	3.571	3.500	1.155	0.063	0.071	-0.008	0.653
Ln(Tenure in years)	141658	2.085	2.197	0.730	0.018	0.014	0.004	0.690
$(\text{Ln(Tenure in years)})^{-1}$	138839	0.548	0.455	0.274	-0.009	-0.003	-0.007	0.493
Callable	141657	0.462	0.000	0.499	0.067	0.020	0.046	0.251
Competitive Offering	140783	0.626	1.000	0.484	0.068	-0.057	0.124	0.036
Insured	141658	0.109	0.000	0.312	0.246	-0.065	0.311	0.118
Semiannual	141658	1.000	1.000	0.020	-0.000	0.000	-0.000	0.717
Trading Yield (%)	830374	2.188	1.919	1.259	-0.196	-0.207	0.012	0.440
Monthly Num. of Trades	848553	6.960	4.000	11.868	-0.111	-0.077	-0.034	0.044
Monthly SD of Price	792105	0.723	0.574	0.649	-0.231	-0.222	-0.008	0.605
PFAS Industry Share	1928	4.266	3.988	1.798	-0.007	-0.008	0.002	0.678
Water Code Violations	1958	2.624	0.000	13.133	-0.317	-0.436	0.118	0.577
Δ Prop. Taxes Per Capita	1929	0.059	0.015	1.192	-1.015	-1.077	0.062	0.784
Δ IGR Per Capita	1930	0.066	0.008	1.659	-0.331	-0.319	-0.011	0.977
Δ Num. Employment	1958	0.007	0.007	0.017	-0.670	-0.185	-0.485	0.123
Δ Num. Estab.	1956	0.015	0.017	0.037	-0.620	-0.608	-0.012	0.979

Table IV: PFAS Contamination and Offering Yields

This table reports the effect of contamination discovery on offering yield to maturities (primary market yields) of municipal bonds. The regression specification follows Equation (5):

$$\text{YTM}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{ Post}_t + \delta \text{ Controls}_{imcst} + \text{Rating}_i + \text{Rating Agency}_i + \text{Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst} ,$$

The outcome variable is the *Offering Yield to Maturity* (*YTM*, in percentages) of bond i issued on date t by municipality m in county c of state s. In Columns (1) and (2), regression sample includes counties contaminated by any of the six PFAS and the bordering uncontaminated counties. In Columns (3) and (4), regression sample includes counties contaminated by PFOA and PFOS and the bordering uncontaminated counties that did not detect any of the six PFAS. $Treatment_{cs}$ 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 CUSIP-level log issuance amount, log bond tenure (in years), inverse of log bond tenure (in years), and binary variables indicating whether the bond is insured, callable, competitively offered, and has semi-annual coupons. $County\ Controls_{cst}$ include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes, per capita inter-governmental revenue transfers, number of establishments, and private-sector employment. All variables are defined in Table (III). All regressions include five fixed effects: county, state × year, rating, rating agency, and capital type. 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.

Contaminant =	Any PFAS		PFOA or PFOS	
	(1)	(2)	(3)	(4)
	YTM	YTM	YTM	YTM
Treatment × Post	0.08***	0.09***	0.07***	0.09***
	(3.58)	(4.37)	(3.41)	(4.11)
Controls	Bond	Bond & County	Bond	Bond & County
FE: County, State × Year, Rating, Rating Agency, Capital-type	Y	Y	Y	Y
Cluster: County	Y	Y	Y	Y
R^2 (Adj.)	0.82	0.82	0.82	0.82
Observations	136125	135212	125137	124410

Table V: Heterogeneous Effects on Offering Yields

This table reports the heterogeneous effects of contamination discovery on offering yields of municipal bonds with different characteristics. Column (1) presents the differential impact on bonds not backed by taxation power relative to general obligation bonds. Column (2) presents the differential impacts on bonds of long maturity ($\geq 15 years$) relative to those of shorter maturities. Column (3) presents the differential impact on bonds from counties whose fraction of revenues received from intergovernmental transfers in the pre-event year 2015 was higher than the cross-sectional median. Column (4) presents the differential impact on bonds from counties with homeownership rate higher than the median rate in the pre-event year 2015. Column (5) presents the differential impact on the bonds issued by municipalities from the states other than the nine classified as proactive in Gao et al. (2019). The regression specification is:

$$\text{YTM}_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t \times \mathbb{X} + \beta_2 \text{ Treatment}_{cs} \times \text{Post}_t + \beta_3 \text{ Treatment}_{cs} \times \mathbb{X} + \beta_4 \text{ Post}_t \times \mathbb{X}$$
$$+ \beta_5 \mathbb{X} + \delta_1 \text{ Controls}_{imcst} + \text{ Rating}_i + \text{ Rating Agency}_i + \text{ Capital-type}_i + \alpha_{cs} + \gamma_{st} + \epsilon_{imcst}$$

The outcome variable is the *Offering Yield to Maturity* (*YTM*, 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 $Treatment_{cs} \times Post_t \times \mathbb{X}$ captures the heterogeneous effects on different bonds characterized by $\mathbb{X}$. $Bond\ Controls_{imcst}$ include CUSIP-level log issuance amount, log bond tenure (in years), inverse of log bond tenure (in years), and binary variables indicating whether the bond is insured, callable, competitively offered, and has semi-annual coupons. $County\ Controls_{cst}$ include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes, per capita inter-governmental revenue transfers, number of establishments, and private-sector employment. All variables are defined in Table (III). All regressions include five fixed effects: county, state × year, rating, rating agency, and capital type. 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.

Third Difference $\mathbb{X}$ =	Non-G.O.	Maturity≥15	High Dependence on Governmental Transfers	Low Homeownership	Non-Proactive
	(1)	(2)	(3)	(4)	(5)
	YTM	YTM	YTM	YTM	YTM
Treatment × Post × $\mathbb{X}$	0.07*	0.07***	0.11**	0.11*	0.06*
	(1.73)	(2.62)	(2.49)	(1.84)	(1.65)
Bond & County Controls	Y	Y	Y	Y	Y
FE: County, State × Year, Rating, Rating Agency, Capital-type	Y	Y	Y	Y	Y
Cluster: County	Y	Y	Y	Y	Y
R^2 (Adj.)	0.82	0.82	0.82	0.82	0.82
Observations	135212	135212	105482	130635	135212

Table VI: Mutual Funds' Allocation to Affected Municipalities

This table reports the effect of contamination discovery on allocation decision of mutual funds in the bonds issued by municipalities from the affected and the bordering, unaffected counties. The regression specification is:

$$\text{Y}_{ifq} = \beta_0 + \beta_1 \text{ Affected Bond}_i \times \text{Post}_q + \gamma \text{ Controls} + \alpha_i + \delta_f + \lambda_q + \epsilon_{ifq}$$

The outcome variable in Columns (1), (3) and (5) is the allocation of fund f's in basis point to bond i in year-quarter q. The outcome variable in Columns (2), (4) and (6) is the natural log of the number of bond i held by fund f in year-quarter q. The regression sample in the first two columns includes all funds, in the middle two columns include only active funds, and the last two columns include only index funds. $Treatment_i$ equals 1 if the 6-digit CUSIP of the bond held by mutual funds matches with 6-digit CUSIP of municipal bonds issued by the municipalities in the contaminated counties and 0 otherwise. $Post_q$ takes the value of 1 for $q \geq$ Q3, 2016 and 0 for the earlier periods. The coefficient associated with $Affected\ Bond_i \times Post_q$ captures the change in mutual fund holding of bonds issued by municipalities in treated counties relative to bordering control counties in the same state before and after the event. *Controls* include management fees, expense ratio, and natural log of one-quarter lagged values of fund's total net assets and underlying bond's market value. All regressions include fund, bond, and year-quarter fixed effects. Standard errors are clustered by fund. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Fund Type =	All Funds		Active Funds		Index Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
	Allocation (bps)	Num. bonds (log)	Allocation (bps)	Num. bonds (log)	Allocation (bps)	Num. bonds (log)
Affected Bond × Post	-0.340*	-0.012***	-0.366*	-0.014***	0.118	0.019
	(-1.81)	(-5.94)	(-1.89)	(-7.29)	(0.17)	(0.82)
Controls	Y	Y	Y	Y	Y	Y
FE: Fund, CUSIP8, Year-Quarter	Y	Y	Y	Y	Y	Y
Cluster: Fund	Y	Y	Y	Y	Y	Y
R^2 (Adj.)	0.80	0.98	0.81	0.98	0.68	0.93
Observations	3193694	3192386	3045880	3044572	147453	147453

Table VII: Banks' Holdings of Municipal Bonds and Loans

This table reports the effect of contamination discovery on banks' supply of capital to municipalities. The regression specification is:

$$\text{Bank Municipal Holdings}_{bq} = \beta_0 + \beta_1 \text{ Treatment}_b \times \text{Post}_q + \delta_1 \text{ Bank Controls}_{bq} + \alpha_b + \gamma_q + \epsilon_{bq}$$

Outcome variable in Column (1) through (3) are respectively, the ratio of held-to-maturity municipal bonds under fair value method (RCFD8497) to bank's total assets; the ratio of held-to-maturity municipal bonds under amortized cost method (RCFD8496) to bank's total assets; and the ratio of municipal loans (RCFD2107) to bank's total assets (RCFD2170). $Treatment_b$ equals 1 if the share of bank's pre-period deposits coming from contaminated counties was higher than average and 0 otherwise. $Post_q$ takes the value of 1 for $q \geq$ Q3, 2016 and 0 for the earlier periods. The coefficient associated with $Treatment_b \times Post_q$ captures the change in bank capital to municipalities before and after the event in banks with greater exposure to polluted counties relative to banks with less exposure. $Bank\ Controls_{bq}$ include net interest margin, return on assets, and the growth rate of total assets. All regressions include bank fixed effects and year-quarter fixed effects. Standard errors are clustered by bank. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Bank Holdings of Municipal Bonds		Bank Loans to Municipalities
	(1)	(2)	(3)
	$\frac{\text{HTM at Fair Value}}{\text{Total Assets}}$ %	$\frac{\text{HTM at Amortized Cost}}{\text{Total Assets}}$ %	$\frac{\text{Loans to Muni}}{\text{Total Assets}}$ %
Treatment × Post	-0.20*	-0.21*	-0.25
	(-1.94)	(-1.97)	(-1.40)
Controls	Y	Y	Y
FE: Bank, Year-Quarter	Y	Y	Y
Cluster: Bank	Y	Y	Y
R^2 (Adj.)	0.91	0.90	0.90
Observations	1413	1413	1413

Table VIII: Out-migration

This table reports the effect of contamination discovery on migration following the framework:

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

Dependent variable in Column (1) is net out-migration from a county in percentages; in Column (2) is adjusted gross income (AGI) of out-migrants − in-migrants, scaled by AGI of out-migrants; in Column (3) is AGI of in-migrants − residents, scaled by AGI of residents; and in Column (4) is AGI of out-migrants − residents, scaled by AGI of residents. $Treatment_{cs}$ 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 annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes, per capita inter-governmental revenue transfers, and number of establishments. All variables are defined in Table (III). 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.

	(1) Out-migration %	(2) $\frac{\text{AGI [Out} - \text{In]}}{\text{AGI [Out]}}$ %	(3) $\frac{\text{AGI [In} - \text{Residents]}}{\text{AGI [Residents]}}$ %	(4) $\frac{\text{AGI [Out} - \text{Residents]}}{\text{AGI [Residents]}}$ %
Treatment × Post	0.11**	2.66*	-0.18***	-0.01
	(2.18)	(1.71)	(-2.76)	(-0.23)
Controls	Y	Y	Y	Y
FE: County, Year	Y	Y	Y	Y
Cluster: County	Y	Y	Y	Y
R^2 (Adj.)	0.65	0.58	0.86	0.67
Observations	3405	3408	3410	3410

Table IX: Response of the Affected Municipalities

This table reports the effect of contamination discovery on public expenditure and employment at the county level following the framework:

$$Y_{cst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \text{ County Controls}_{cst} + \alpha_{cs} + \gamma_t + \epsilon_{cst}.$$

Public Expenditure is expressed as *per capita* dollar amounts aggregated to the county level. *Total Expenditure* is the sum of all expenditures. *General Expenditure* is expenditures on general government activities, which is total expenditure minus transfers to utilities, liquor stores, and social insurance trust sectors. The difference between *Direct General Expenditure* and *General Expenditure* is intergovernmental expenditures. Direct expenditures include current expenditures used to pay employees, purchase supplies and hire contractors and capital outlay expenditures used to build and purchase long term assets. *Public Employment* refers to full-time equivalent public sector employment, measured per 1,000 population. *Share of Public Emp.* is the ratio full-time-equivalent public employment to total employment in a county. $Treatment_{cs}$ 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 annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes and per capita inter-governmental revenue transfers in Column (4) and (5), and the annual growth rates of number of establishments in addition in Column (1) to (3). All variables are defined in Table (III). 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.

	Public Expenditure (USD per capita)			Public Employment	
	(1)	(2)	(3)	(4)	(5)
	Total	General	Direct Genetal	Emp. per 1,000	Share of Public Emp.
Treatment × Post	-125.69**	-103.96*	-94.30*	-2.15***	-0.01***
	(-2.18)	(-1.95)	(-1.80)	(-4.40)	(-4.85)
Controls	Y	Y	Y	Y	Y
FE: County, Year	Y	Y	Y	Y	Y
Cluster: County	Y	Y	Y	Y	Y
R^2 (Adj.)	0.97	0.96	0.96	0.87	0.79
Observations	3410	3410	3410	2943	2943

Table X: Effect on Bond Borrowing Amount

This table reports the effect of contamination discovery on the changes in the amount of amount borrowed for long and short term. The regression is conducted on a county×year panel using the equation:

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

In Column (1) the outcome variable is total issue amount, and in Column (2) it is county-aggregated ratio of annual issuance amount raised for short term (bond maturity <10 years) to the amounts raised for long term (bond maturity ≥10 years). $Treatment_{cs}$ 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 municipality bond issuance before and after the event in treated counties relative to bordering control counties in the same state. $County\ Controls_{cst}$ include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes, per capita inter-governmental revenue transfers, number of establishments, and private-sector employment. All variables are defined in Table (III). All regressions include county fixed effects and state × year fixed effects. Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Issue Amount (all maturities)	$\frac{\text{Issue Amount} < 10 years}{\text{Issue Amount} \geq 10 years}$
	(1)	(2)
Treatment × Post	-0.011	0.527**
	(-0.13)	(2.00)
County Controls	Y	Y
FE: County, State × Year	Y	Y
Cluster: County	Y	Y
R^2 (Adj.)	0.79	0.10
Observations	1810	1709

Table XI: Treatment Effect on Trading Yields

This table reports the effect of contamination discovery on the trading yields of municipal bonds in the secondary market. The regression Equation is (10):

$$Y_{imcst} = \beta_0 + \beta_1 \text{ Treatment}_{cs} \times \text{Post}_t + \delta_1 \text{ Bond Controls}_{imcst}$$
$$+ \delta_2 \text{ County Controls}_{cst} + \alpha_{imcs} + \gamma_{st} + \epsilon_{imcst}$$

The outcome variable in Column (1) is raw trading yields and in Column (2) is trading yield spreads. Trading yield for a bond i is calculated monthly as the volume-weighted average transaction yield (in percentage points) in month t issued by municipality m in county c of state s. Trading yield spread for a bond i is calculated monthly as the volume-weighted average of the difference between the raw trading yield and the same-date linearly interpolated yield on a maturity-matched treasury bond. $Treatment_{cs}$ 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 or trading yield spread before and after the event in treated counties relative to bordering control counties in the same state. $Bond\ Controls_{imcst}$ include log of the remaining maturity (in years) on the transaction day, and inverse of the remaining maturity (in years) on the transaction day, monthly standard deviation of the bond's dollar transaction prices, and number of trades in the transaction month. $County\ Controls_{cst}$ include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, and the annual growth rates of per capita property taxes, per capita inter-governmental revenue transfers, number of establishments, and private-sector employment. All variables are defined in Table (III). All regressions include CUSIP fixed effects and state × year fixed effects. Standard errors are clustered by CUSIP. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	Trading Yield	Trading Yield Spread
Treatment × Post	0.016**	0.017*
	(2.35)	(1.84)
Controls	Y	Y
FE: Bond, State × Year	Y	Y
Cluster: Cusip	Y	Y
R^2 (Adj.)	0.79	0.64
Observations	1215402	1204959