

Municipal and Economic Consequences of PFAS Contamination Discovery*

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December 2024 [[Latest Version](#)]

Abstract

Hazardous but previously unmonitored and unregulated, per- and polyfluoroalkyl substances (PFAS) were detected in 2016 in municipal drinking water systems across 33 US states during the first-ever PFAS testing. A paired-county difference-in-differences design that compares contaminated counties with neighboring, same-state uncontaminated counties shows that the contamination discovery raised municipal bond offering yields by 14 basis points. Municipal revenues, taxes, employment, and expenditures declined, while population out-migration increased. Consistent with the contamination requiring a higher compensating wage differential, wages in tradable industries rose, but job creation fell, and firm closures increased. Self-employment increased as well, indicating a heightened local unemployment risk.

JEL Classification: G14, H72, H74, Q53, Q58.

Keywords: Municipal Bonds, PFAS (Forever Chemicals) Contamination, Drinking Water Contamination.

*We thank Utpal Bhattacharya, Jie (Jay) Cao (discussant), Vidhan Goyal, Hyemin Kim (discussant), Yufeng Sophia Mao (discussant), Abhiroop Mukherjee, Arkodipta Sarkar, Yue Yu (discussant), Alminas Žaldokas, and the participants at Australasian Finance & Banking Conference 2023, HKUST brownbag seminar, SMU Summer Finance Research Camp 2023, and North American Meeting of Urban Economics Association 2023 for their valuable feedback. This work was supported by research grant 22-LKCSB-SMU-027 at Singapore Management University from the Ministry of Education Academic Research Fund Tier 1. All errors are our own.

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For 20 years a farmer in Maine fertilized his fields with treated sewage sludge as part of a state fertilizer program from the 1980's. Sourced from local municipalities, the sludge was contaminated with PFAS. After the EPA's 2016 testing detected PFAS in nearby town's water wells, the farmer found the milk from his farm contained dangerously high levels of PFAS, entire 15 years after he had stopped using the contaminated sludge in 2004. The century-old farm is now permanently closed.

—EcoWatch Oct 15, 2019

We examine the effects of discovery of contamination by previously unmonitored and unregulated but hazardous chemicals known as per- and polyfluoroalkyl substances (PFAS) on municipalities and local economic conditions. PFAS are a part of a broader class of chemicals characterized as emerging pollutants, a designation that reflects growing concern of their hazardous effects on both environment and human health. PFAS remained unregulated in the U.S. until 2024. Although manufacturing of two of the most well known PFAS chemicals—perfluorooctanoic acid (PFOA) and perfluorooctane sulfonate (PFOS)—has largely been phased out in the U.S. since around 2008 ([ATSDR, 2021](#), p. 654), over 1,100 locations across the country have been discovered to be contaminated with PFAS by 2022 and new locations continue to be identified ([PFAS Project Lab, 2023a](#)).

We focus on PFAS contamination because of the unique challenges faced by the contaminated areas after discovery. First, remediating the contamination is prohibitively costly and uncertain, if at all possible.¹ Second, while the contamination discovery necessitates immediate remediation, recovering the costs through litigation and regulatory penalties is uncertain and may take a long time, if it happens at all.² This

¹ Removing PFAS from effluent and landfills in Minnesota is estimated to cost \$14 billion and \$105 million respectively ([MPCA, 2023](#), p. 3). Nationwide estimates for PFOA and PFOS removal vary from \$3 billion to \$38 billion depending on the allowable PFAS concentration in drinking water, and treatment technology installation would cost more than \$370 billion in investment and over \$12 billion in annual operations and maintenance ([AWWA, 2019](#)). The estimates vary widely because of uncertainty in allowable standards and the appropriate cleanup and treatment procedures vary by contaminants. Footnote 6 outlines several examples of budgetary constraints arising from anticipated cleanup costs.

² [Johnson \(2020\)](#) explain, from a legal perspective, why the government's ability to respond to PFAS contamination is limited under the two main environmental statutes currently in force in the U.S.: the Safe Drinking Water Act (SDWA) and the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA). Popular media estimates that more than 15,000 nationwide claims related to PFAS contamination are ongoing against DuPont, Chemours, Corteva, and 3M, the major manufacturers of PFAS. 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](#)). Even the combined assets of all these manufacturers may prove insufficient to clean all the contamination sites in the U.S.

is partly due to the fact that PFAS usage was not restricted in the past, enforceable safe exposure limits were not established, and contamination could arise from numerous sources, including production, use, and disposal of PFAS-containing products.³ The extremely long life of these chemicals in the natural environment further complicates identification of the contamination source.⁴ Hence we set out to understand the effects such unexpected contamination discoveries have on the economic health of the contaminated areas. In doing so, we aim to draw lessons on how local governments and the associated real economy could be affected as more PFAS contamination sites continue to be discovered not only in the U.S. but also in other countries. These can also help inform policy responses in managing future contamination sites.

We identify multifaceted adverse effects following the 2016 revelation of drinking water contamination during the first-ever nationwide PFAS testing in the U.S. Offering yields on municipal bonds issued by municipalities in contaminated counties increased, and the rise was greater for bonds and municipalities characterized by factors associated with credit risk. While one might expect the cleanup and treatment costs to primarily burden only the municipalities responsible for water infrastructure, our findings indicate that *all* municipalities in the contaminated counties were impacted. This broader impact arises from two key factors. First, bond financing for such expenditures is often raised by the broader city governments than water-related municipalities.⁵ Second, the deteriorating economic conditions reduce revenues and tax collections for all municipalities, adding to their budgetary imbalances. We find

³ For instance, contamination could originate from factories manufacturing PFAS-based products, households using such products, or from airports and military bases utilizing PFAS-based firefighting foams during drills. The challenge of pinpointing the sources of contamination and identifying effective regulatory remedies is highlighted in a statement from the Zone 7 Water Agency of the City of Pleasanton, whose drinking water was contaminated with PFAS: “Maybe some [of the PFAS came] from a landfill, maybe some from the airport, maybe some from people doing laundry with 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](#)).

⁴ Due to their remarkable resistance to natural degradation, these chemicals are colloquially referred to as “Forever Chemicals”. Their persistence in the environment is so extensive that determining their half-life has proven difficult in the past ([NIEHS, 2019](#), p. 1).

⁵ For example, after the contamination discovery in Hampden County, Massachusetts, the City of Westfield—not a dedicated water municipality—issued \$13 million in bonds to address the contamination ([Hope E. Tremblay, Jun. 29, 2018](#)).

that municipal revenues and taxes declined, partly due to heightened net population out-migration after the event. Faced with higher borrowing costs and lower revenues, municipalities curtailed public expenditure and employment, even after accounting for population changes. In terms of business environment, while average wages in tradable industries rose, job creation in the sector fell, and firm and establishment closures rose—consistent with workers demanding higher compensating differentials to continue working in contaminated areas, rendering some firms non-viable. Self-employment also rose after the event, reflecting higher unemployment risk. Anecdotal evidence suggests that the of clean up costs of contamination not only created budgetary constraints even for counties,⁶ but even led to abandonment of planned public investment.⁷ In all, beyond raising municipal offering yields through reduced revenues (leading to heightened credit risk), the worsening of economic outcomes in industries emphasize the broader impacts of the contamination discovery.

We further examine the role of capital supply and demand factors in driving the yield increases. On the supply side, active mutual funds reduced their holdings of previously issued bonds from affected municipalities relative to those from unaffected ones. On the demand side, while total borrowing amounts remained unchanged, long-term bond issuance rose significantly in affected counties, likely to support financing for water-related infrastructure.

To lend causal interpretation to these findings, we use a paired-county difference-in-differences (DD) approach utilizing the drinking water contamination revealed in August 2016. Environmental Protection Agency (EPA) tested nationwide public drinking water systems for PFAS from 2013 to 2015 under the third Unregulated

⁶ New Hampshire postponed an enforceable limit on PFAS itself fearing prohibitive expenses of compliance ([NHDES, 2020](#); [Ropeik, Jul 16, 2019](#)). Even municipalities from considerably wealthier areas such as Massachusetts have expressed the exorbitant cleanup costs ([MMA, Feb 28, 2020](#)). The Brunswick county, North Carolina estimated that removing a specific PFAS would require about \$100 million in investment and \$3 million in annual maintenance ([NAC, Apr 15, 2019](#)). 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](#)).

⁷ 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](#)).

Contaminant Monitoring Rule (UCMR 3) program. The testing revealed in August 2016 that 200 counties across 33 states had their water supply systems contaminated with the PFAS. This revelation of the contamination status of the counties is the event in our DD approach, as opposed to the contamination itself, which occurred at unknown times in the past.⁸ These contaminated counties, and all local municipal issuers within such counties, are classified as treated. The counties bordering these treated counties lying within the state borders that were uncontaminated are classified as control. For every cluster of geographically contiguous treated and control counties, we form county pairs by repeatedly selecting the treated county for every unique control county, similar to the approach in [Dube, Lester, and Reich \(2010\)](#). The sample period runs from 2013 to 2018.

We argue that this revelation of the contamination status can be considered to mimic an exogenous change in the information available to the market for several reasons. First, PFAS had not been tested for prior to this event. Second, the causes of the contamination are largely unknown and uncertain.⁹ Third, safe limits for PFAS concentrations in drinking water had not been established, which undermined any private incentives to proactively test nationwide drinking water systems in anticipation of the EPA's testing and potentially profit from the subsequent release of results. Moreover, the testing process itself was costly, with the EPA spending \$87 million on PFAS testing ([GAO, 2014](#), p. 2), further diminishing private sector incentives to conduct such tests independently. Fourth, even the technology and procedure to detect

⁸ Similar empirical approach has been used in several studies to derive causal estimates. [Gormley and Matsa \(2011\)](#) and [Lam \(2022\)](#) utilize the discovery of carcinogen status of chemicals, where those firms are considered treated who were already using these chemicals. In household finance literature, [Di Maggio et al. \(2017\)](#), [Fuster and Willen \(2017\)](#), and [Gupta \(2019\)](#) use contemporary changes in interest rates to mimic exogenous variations in monthly mortgage repayments of households who took adjustable rate mortgages in the past (instead of fixed rate mortgages).

⁹ As discussed previously, determining why some drinking water systems were contaminated while others were not is challenging, given the widespread use of PFAS in numerous consumer and industrial applications over more than five decades. So while we do not attempt to identify the precise source of the contamination, we do observe a positive association between the share of PFAS-related industries in a county from 1998 to 2005 and the discovery of contamination in 2016. See Section 1.4. Additionally, the scientific understanding of how PFAS accumulates in the environment after release is still evolving ([Abunada, Alazaiza, and Bashir, 2020](#); [Ahrens and Bundschuh, 2014](#)).

PFAS in water were not well-established until the testing by EPA, because the technical standards were not available ([Dorrance, Kellogg, and Love, 2017](#), p. 294).

We however are careful to not suggest that the contamination itself was exogenous to all observable or unobservable characteristics of the counties. We find that a positive association between the share of PFAS-related industries from 1998 to 2005 and the contamination discovery in 2016. More relevant to our DD estimation approach, there is no difference in the pre-treatment trends between the contaminated and control counties across a range of county-level economic variables, including employment, number of establishments, share of PFAS-related industries, and the quality of drinking water infrastructure. Furthermore, since both treated and the control counties are from the same state and are geographically contiguous, they are subject to the same state-level fiscal and municipality-related policies and local economic trends. Also, the DD strategy differences out the effect of any national or state-level factors, such as gubernatorial elections or the surprise result of the 2016 presidential election.

We estimate that municipal issuers from the contaminated counties experienced an average increase in offering yields of 13 to 14 basis points (bps), a 6.2% increase over pre-event yields, relative to issuers from bordering uncontaminated counties within the same state. This increase is roughly equivalent to the yield change that would occur if the S&P credit rating of a typical municipal bond in the sample from the pre-event period were to drop by three notches, from AAA to BBB. The estimation specifications account for a host of bond characteristics and county-level economic conditions, and include granular fixed effects for credit rating \times rating agency, county, county pair \times year, and the type of capital underlying the bond (new filing or refunding).

Similar to the mechanism in [Chordia, Jeung, and Pati \(2022\)](#), we hypothesize that higher bond offering yields result from increased municipal credit risk following the contamination discovery, driven by deteriorating economic outcomes in the county. These outcomes lead to lower expected future municipal revenues, creating imbalances in current and future operational budgets. As municipalities are expected to balance their operational budgets and typically require voter approval for long-term

borrowings, which are necessary to finance infrastructure—subject to state policies and local statutes ([Ang, Green, Longstaff, and Xing, 2017](#); [Haughwout, Hyman, and Shachar, 2021](#))—their credit risk increases after the event. Although unquantifiable, uncertainty over the level of fiscal support from state and federal governments likely heightened investors’ recognition of the credit risk. Using a Poisson pseudo-maximum likelihood (PPML) regression of ratings, we find that numerical ratings increased by 4.3%, indicating that credit risk on new bonds from issued from municipalities from contaminated counties increased.

To further reaffirm the credit risk hypothesis, we rely on the idea that offering yields of municipal bonds reflect the likelihood that local government net cash flows will be sufficient to make debt repayments ([Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2023](#), p. 2). Accordingly, we conduct several heterogeneity tests using a triple difference specification that utilizes the municipal bond market characteristics argued to be associated with credit risk ([K. R. Cornaggia, Hund, Nguyen, and Ye, 2021](#); [K. Cornaggia, Li, and Ye, 2022](#); [Gao, Lee, and Murphy, 2020](#)). We find that the offering yields increased more for non-general obligation bonds (relative to general obligation bonds), and bonds from states without proactive policies to support distressed municipalities, and also from counties contaminated with a larger number of PFAS chemicals. Thus, investors’ heterogeneous pricing response to the contamination discovery varies in sync with these factors associated with credit risk.

To explore the role of capital supply in raising offering yields, we argue that municipal capital suppliers demand compensation for the increased credit risk of the affected municipalities. We analyze changes in municipal bond holdings of mutual funds, an important class of investor ([Adelino, Cheong, Choi, and Oh, 2023](#)). Active mutual funds reduced their holdings of bonds issued prior to the start of the sample period from contaminated counties relative to those from control counties, while index funds and exchange-traded funds (ETFs), which typically track benchmarks, did not.¹⁰

¹⁰ The reduction in municipal bond holdings by mutual funds does not contradict [K. R. Cornaggia et al. \(2021, sec. 5.4.2\)](#), who find that offering yields of bonds held by institutional investors are less sensitive to local opioid shocks due to their lower capital constraints and diversified portfolios across locations and asset classes. Note that our analysis focuses specifically on portfolio adjustments of mutual funds

Examining household investors, another key source of municipal capital, we find that the increase in yields was smaller for bonds issued by municipalities from counties with high homeownership rates, and high social cohesion, measured as support ratio and clustering (Chetty et al., 2022b). These socio-economic characteristics likely provide greater nonpecuniary utility to resident households, incentivizing them to continue investing in local municipal bonds and tempering the increase in offering yields following the contamination discovery (K. R. Cornaggia et al., 2021).

We next examine the effects of contamination discovery on broader economic outcomes. We find that contaminated counties experienced an increase of 2.4% in net population out-migration after the event relative to the control counties. This effect which is almost 26% larger than the rise in in-migration of 1.9% observed after municipal credit rating upgrades (J. Cornaggia, Gustafson, Israelsen, and Ye, 2019, p. 17) In line with the heightened out-migration, municipal revenues, total taxes, and property taxes declined by approximately 4 to 5% following the event, and municipalities curtailed public expenditure and employment respectively by about 3% and 11% in response. We obtain these reductions after accounting for the increased population out-migration, indicating that the cuts were more than what could be explained by the shrinking resident population alone. We attribute the curtailment to both the increased borrowing costs municipalities faced in the primary bond market and decline in revenues caused by increased population net out-migration by 2.4% and worsening of firm dynamics discussed below. Such reductions are detrimental for the local economic growth due to their fiscal expenditure multiplier effect (Adelino, Cunha, and Ferreira, 2017; Dagostino, 2018). We also find that the participation in health insurance usage increased in the contaminated counties after the event, consistent with households becoming aware of the contamination and its adverse health effects.

(not other institutional investors), utilizing *within-bond holding changes over time* for bonds issued prior to the sample period. In contrast, their study examines *across-bond differences in offering yields*, comparing yields of bonds more likely to be held by all institutional investors combined with those less likely to be held at or around issuance.

The contamination discovery also affected private firms. In line with the idea that workers would demand a higher compensating differential to continue working in contaminated areas, we find that tradable industries (where employees are largely skilled) experienced a 5% rise in payrolls, but also a 4% rise in firms closures and a 7% decline in job creation, accounting for the contemporaneous changes in control counties and in nontradable industries. These patterns suggest that some firms had to close operations due to the rise in cost of labor. We also document 1% increase in both the number of no-employee (sole-owner) firms and self-employed individuals in contaminated counties, consistent with an increase in unemployment risk ([Hou, Jonsson, Li, and Ouyang, 2025](#)).

Our primary contribution lies in documenting the causal adverse effects of PFAS contamination discovery on local municipalities and economic outcomes. While our findings regarding the impact on municipal borrowing costs are similar in spirit to those of [K. R. Cornaggia et al. \(2021\)](#) regarding the effects of the opioid crisis, we uncover several novel adverse movements in real economic outcomes. These include changes in municipal operations—such as revenues, expenditures, and public employment—and, more importantly, impacts on local population migration, firm dynamics, and unemployment risk.¹¹ The identification and quantification of the shifts in these real outcomes at the local level remain novel and cannot be directly inferred from (i) the effects of long-run sea-level rise on municipal borrowing costs for seventeen major U.S. coastal cities ([Painter, 2020](#)) and on secondary market yield spreads for school districts bonds ([Goldsmith-Pinkham et al., 2023](#)); or (ii) the effects of climate regulation risks on corporate bond yields ([Seltzer, Starks, and Zhu, 2022](#)). These findings also diverge from [Adelino et al. \(2017\)](#), who focus specifically on linking financing constraints of municipalities on public expenditures, employment, and income. In contrast, we attribute both the rise in municipal borrowing costs

¹¹ Additionally, while opioid crisis is a severe health crisis in the U.S., PFAS contamination is a global concern, with contamination being discovered in European Union ([The Forever Pollution Project, 2024](#); [ECHA, 2024](#)), China ([Ao et al., 2019](#)), and several developing countries ([Adewuyi and Li, 2024](#)). Moreover, as we discussed earlier, unlike opioids, PFAS were ubiquitous and were largely unregulated in the U.S. until 2024, and continue to be unregulated in other countries, posing significant challenges for effective governmental response ([Johnson, 2020](#)).

(financing constraint) and the subsequent worsening of economic outcomes to the discovery of PFAS contamination. We are unable to isolate the effect arising solely from financing constraints (see footnote 13 for more details).

Our findings also differ from [Adelino et al. \(2017\)](#) in the sense that their focus is on linking financing constraints to municipal expenditures and employment, whereas we attribute both the increase in municipal borrowing costs and the subsequent worsening of economic outcomes to the contamination discovery.

Our paper adds to the literature studying the effects of factors related to municipal finance on primary market borrowings of municipal bonds.¹² The primary difference from the prior studies lies in the nature of PFAS contamination, which may have occurred in the past but adversely impacts economic outcomes in the counties discovering these toxic inheritances in the present. Our findings are closely related to the literature exploring the link between municipal bond markets and real economic 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](#)). However, our results differ from these studies in one key aspect: the adverse effects on real economic outcomes in our study are not solely driven by the increase in municipal bond yields. Instead, we believe that the discovery of contamination itself plays a significant role.¹³ Our finding that mutual funds reduce their holding of bonds issued by the affected municipalities speaks to the recent 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, O'Hara, and Zhou, 2023](#)). Finally, our paper adds to the literature studying economic effects of drinking water pollution. PFAS contamination discovery of Paulsboro water system, New

¹² Offering yields of municipal bonds have been shown to be affected by information intermediaries ([Gao et al., 2020](#); [J. Cornaggia, Cornaggia, and Israelsen, 2018](#); [J. Cornaggia et al., 2019](#)), policies of state for distressed municipalities ([Gao, Lee, and Murphy, 2019](#)), underwriters ([Garrett and Ivanov, 2022](#); [Garrett, 2021](#); [Butler, 2008](#)), municipal bonds' tax treatment ([Garrett, Ordin, Roberts, and Suárez Serrato, 2023](#)), and corruption ([Butler, Fauver, and Mortal, 2009](#)).

¹³ While decomposing the effects into the two potential drivers—(i) higher bond yields induced reduction in municipal expenditure and associated fiscal multiplier effects; and (ii) the contamination discovery itself—could be valuable, we acknowledge that our empirical setup is not suited for such a decomposition. Consequently, we are unable to isolate the specific contributions of these factors.

Jersey lowered prices of nearby houses ([Marcus and Mueller, 2023](#)). Groundwater contamination also has similar effects ([Muehlenbachs, Spiller, and Timmins, 2015](#)). Moreover, lead contamination results in lower consumer credit scores ([Gorton and Pinkovskiy, 2021](#)), higher healthcare demand ([Danagouliau, Grossman, and Slusky, 2020](#)) and public expenditure ([Christensen, Keiser, and Lade, 2019](#)).

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. PFAS are currently being researched for adverse developmental, reproductive, and systemic health consequences ([EPA, November 2017](#)).¹⁴ 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.

[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

¹⁴ See [Dorrance et al. \(2017\)](#) for manufacturing history, chemical properties and remediation challenges of PFAS, [Johnson \(2020\)](#) for challenges of regulating them, and [DeWitt et al. \(2015\)](#) for a comprehensive technical discussion of its health effects.

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: Timeline of UCMR Activities). This program tested for six PFAS chemicals: PFOA, PFOS, PFHpA, PFHxS, PFNA, and PFBS.¹⁵ 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.¹⁶ 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 paired-county DD design around the detection of PFAS in drinking water under the UCMR (3) program. The treatment group comprises the counties revealed to be contaminated under UCMR (3), while the control group consists of neighboring counties within the same state that share borders with the contaminated counties but were not identified as having PFAS contamination. It is to be noted that actual contamination occurred at unknown times in the past. To construct treated and control county pairs, we form within-state contiguous county pairings, allowing a county to appear multiple times in the sample depending on the number of uncontaminated neighboring counties within the state it shares its border with. This strategy of comparing within-state bordering county-pairs is a variation of the empirical strategy used in [Dube et al. \(2010\)](#). Consequently, our dataset has 200 treated counties across 33 states, 426 control counties, and 592 distinct county pairs. Figure

¹⁵ 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.

¹⁶ 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.

II shows these counties on the map of the contiguous U.S. All local governments in a county, i.e., municipalities, cities, townships and other public issuers are assigned the treated or control status based on the contamination status of county. We focus exclusively on local sub-county-level municipalities, as they are more likely to experience the economic constraints resulting from the contamination compared to county-level governments. August 9, 2016 serves as the event date. Our sample runs from 2013 till 2018.

[Insert Figure II About Here]

We utilize two-way fixed-effects (TWFE) specification taking the general form as follows:

$$Y_{imcpt} = \alpha_0 + \beta_1 \text{Treatment}_c \times \text{Post}_t + \delta \text{Controls} + \text{Rating} \times \text{Agency}_i + \text{Capital-type}_i + \alpha_c + \gamma_{pt} + \epsilon_{imcpt} , \quad (1)$$

where Y_{imcpt} is the offering yield of municipal bond i issued on date t by municipality m from county c of county-pair p . Treatment_c equals 1 if the drinking water supply of county c 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.¹⁷ *Controls* vary across specifications and consist of a host of bond characteristics and county-level socioeconomic indicators.

$\text{Rating} \times \text{Agency}_i$ represents rating by rating agency fixed effects. These account for the fixed differences in the outcome variable for bonds rated differently and rated by different agencies. Capital-type_i represents the fixed effects for the type of capital, “New Filing” or “Refunding”. α_c represents county fixed effects. These account for any inherent time-invariable differences across counties, including their status as urban or rural counties. γ_{pt} denotes *Pair*×*Year* fixed effects. These flexibly account for any

¹⁷ 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.

pair-specific economic shocks or any policy changes, even if they arise in different years. Subscript p in Y_{imcpt} and γ_{pt} denotes that counties (and hence bonds issued by municipalities from there) may be repeated for all county pairs they are part of. Finally, to account for cross-sectional correlation, standard errors are clustered at the county level in all regression specifications.

1.3 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 outcome variables 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:

$$\begin{aligned} \text{YTM}_{imcpt} = & \alpha_0 + \sum_{k=T-3, k \neq T}^{T+3} \beta_k \text{Treatment}_c \times \text{Year}_k + \text{Controls}_{imcpt} \\ & + \text{Rating} \times \text{Rating Agency}_i + \text{Capital-type}_i + \alpha_c + \gamma_{pt} + \epsilon_{imcpt}, \end{aligned} \quad (2)$$

where T = event year, and Year_k is one when $t = T - k$. *Controls* are defined in Section 3.1.¹⁸

The plot of the estimates of β 's in Panel A of Figure III 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, indicating the yields for the two sets of bonds were not experiencing differential trends before the event.

[Insert Figure III About Here]

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

$$\text{Outcome}_{cpt} = \alpha_0 + \sum_{k=2013, k \neq 2015}^{2018} \beta_k \text{Treatment}_c \times \text{Year}_k + \alpha_c + \gamma_{pt} + \epsilon_{cpt} \quad (3)$$

¹⁸ Since the event happens mid-year on August 16, 2016, we use synthetic year variable based on 365-day intervals counting from the event date to implement the indicators and fixed effects for year. Section 3.1 further elaborates on this design choice.

Each of the Panel B through E of Figure III shows the plot of β 's for the four county-level outcomes—share of PFAS industries, number of drinking water violation per million population, number of establishments (in natural log), and number of employment (in natural log). 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.

1.4 Could Industrial Activities or Water 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, 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 EPA's recently published list of industries potentially handling and/or releasing PFAS. We focus on the four-digit NAICS codes of these industries. 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 four-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* \times *NAICS* \times *Year* data become available in the County Business Patterns. The regression specification is:

$$\text{Treatment}_{cs} = \alpha_0 + \beta_1 \times \text{PFAS-share}_{cs} + \gamma_s + \epsilon_{cs}. \quad (4)$$

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 IV shows the coefficients β_1 for each year and the 95% and 99% confidence intervals based on standard errors clustered at the county level. We see that the share of these industries over 1998 till 2005 in a county does predict the contamination.

We repeat this analysis with the quality of drinking water infrastructure in a county. We measure the infrastructure quality by the number of annual per million population violations of health-related drinking water codes.¹⁹ 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 IV. The estimates suggest that the quality of drinking water infrastructure does not predict the contamination.

[Insert Figure IV About Here]

Although our identification strategy relies on the discovery of contamination, not the contamination per se, 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.

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 drinking water along with the zip codes of the water service areas. 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

¹⁹ 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.

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, over 87 times the current legally enforceable level (4 ppt for PFOA).

[Insert Table II About Here]

We assemble municipal bond issuance data from 2013 till 2018 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.²⁰ After linking municipalities to their respective counties, we classify municipalities headquartered in zip codes within 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, bonds whose capital type is neither new filing nor refunding, and bonds whose coupon is neither paid semiannually at a fixed rate nor paid exclusively at maturity. Additionally, we exclude all state and federal issuers, as well as county issuers. County issuers are excluded because local sub-county-level municipalities are more likely to face the economic

²⁰ We exclude municipalities headquartered in zip codes that span boundaries of both treated and control counties. Additionally, we omit all school district bonds, as a typical school district in the 33-sample states covers an average of 1.6 counties. These bonds are identified by purpose codes beginning with the letter “E.”

constraints resulting from contamination than counties themselves. Specifically, we remove issuers identified in the SDC dataset with issuer type codes 10, 11, 13, 19, and 20. The resulting bonds constitute the sample for our analysis of primary market offering yields to maturities. It consists of 52,650 bonds (at nine character CUSIP level) issued by 1,642 municipalities from 153 counties in the treated group and 43,679 bonds issued by 1,408 municipalities from 257 counties in the control group. The upper panel of Table III presents key statistics on these new bond issues. We see that a typical new municipal bond has an offering yield to maturity at issuance (primary market yield) of 2.33%, coupon of 3.51%, $\text{Ln}(\text{tenure in years})$ of 2.08, and $\text{Ln}(\text{amount})$ of 13.46. Another financial dataset we use is municipal bond holdings by mutual funds. The data come from Center for Research in Security Prices (CRSP) mutual fund database which we link to the municipal bonds using the 6-character CUSIP.

[Insert Table III About Here]

The lower panel of Table III reports the summary statistics of county-level socioeconomic variables. We assemble these data from various sources. Population data come from Census Bureau’s annual county resident population estimates. Personal income data come from the Bureau of Economic Analysis. The data on establishments, employment, and payroll come from Census Bureau’s county business patterns data. Firm death and job creation and destruction data are from business dynamics statistics. We obtain the classification of 4-digit NAICS industries into tradable and non-tradable industries from Mian and Sufi (2014) based on top and bottom quartile of by geographical concentration. Self-employment data come from Census Bureau’s nonemployer statistics and Inland Revenue Service’s (IRS) record of returns with self-employment tax. Similarly, we construct our homeownership rate as the fraction of total returns that have mortgage deductions. IRS’ statistics of income (SOI) also provide county-level migration data. Local government revenue, expenditure, 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. We

use county clustering and support ratio from Chetty et al. (2022a) and Chetty et al. (2022b) to proxy for social capital. Finally, we measure county-level quality of drinking water infrastructure by the number of health-related violations per million population of the U.S. Safe Drinking Water Act reported under the safe drinking water information system. According to the list of industries potentially handling or releasing PFAS published by EPA, we calculate the PFAS industry share for each county. We use the toxic release inventory data to identify the presence of a DuPont, 3M, or Chemours facility in a county. We use county FIPS to link all these datasets together.

3 Effects of PFAS Contamination Discovery on Municipal Finances

3.1 Effect on Offering Yields to Maturity

We begin the empirical analysis with evaluating how the offering yields to maturity changed after the contamination discovery. We use the following regression:

$$\begin{aligned} YTM_{imcpt} = & \alpha_0 + \beta_1 \text{Treatment}_c \times \text{Post}_t + \text{Bond and County Controls} \\ & + \text{Capital}_i + \text{Rating} \times \text{Agency}_i + \alpha_c + \gamma_{pt} + \epsilon_{imcpt}, \end{aligned} \quad (5)$$

where YTM_{imcpt} is the offering yield to maturity of bond i (at the CUSIP level) issued by municipality m from county c of county-pair p in year t . Subscript p in YTM_{imcpt} and γ_{pt} denotes that counties (and hence bonds issued by municipalities from there) may be repeated for all county pairs they are part of. β_1 is the coefficient of interest. *Bond and County Controls* include CUSIP-level bond amount (in log), tenure in years (in log), inverse of log bond tenure (in years), indicators for whether the bond is callable, insured, and whether the bond offering type is competitive or negotiated. Additionally, seven county-level variables are included in it: the share of PFAS-related industries (the ratio of the number of establishments in the PFAS-handling industries identified at 4-digit NAICS codes to the total number of establishments), per capita number of health-related drinking water code violations, an indicator for whether the county has a factory owned by three main PFAS manufacturers (3M, DuPont, and Chemours), and natural log of the number of employment, establishments, population, and county-

aggregated personal income. $Rating \times Agency_i$ introduces fixed effects for each rating category assigned by each of the three rating agencies, S&P, Moody's, and Fitch.²¹ $Capital_i$ denotes capital-type fixed effects, accounting for differences across issues of refunding and new filing. α_c denotes county fixed effects, and γ_{pt} denotes $Pair \times Year$ fixed effects.²²

[Insert Table IV about here]

Table IV shows the results of the above regression. The specification in columns (1) and (4) include only bond-level covariates, and those in columns (2) and (5) include both bond- and county-level covariates. Classifying contamination with any of the six PFAS as treated, the estimates of β_1 in columns (1) and (2) suggest that a new bond issued by a municipality in a contaminated county experienced an increase of 10 to 13 bps in offering yields to maturity relative to a municipality from a neighboring uncontaminated county after the discovery of the contamination. Our preferred estimate is the latter from column (2), as this specification accounts for county-level economic trends. This estimate is robust to changing local economic trends, state-level fiscal changes, and any nationwide change, such as the surprise result in the 2016 presidential election.²³

Recall that our empirical approach relies on the assumption that the information on the PFAS contamination status of the counties was exogenous, even though the contamination itself could have occurred endogenously in the past. We argue that this assumption is more likely to hold for the two legacy PFAS, PFOA and PFOS, because

²¹ Rating takes the value of 1 for Aaa rating, 2 for Aa1, ... and, 10 for Baa3. All bonds rated below this (just 0.1% of the sample) and unrated bonds together are assigned a separate numerical rating category for the purpose of implementing the rating category fixed effects.

²² Since municipal bonds can be issued at any date in a year and since the event in our setting occurred mid-year on August 9, 2016, the definition of *Post* would not align with year fixed effects (in $Pair \times Year$) if we used calendar year to implement the year fixed effects, creating issues with the estimates of β_1 . Hence, for all regressions where the outcome variable is related to municipal bonds, we use synthetic year variable based on 365-day intervals counting from the event date to implement the year fixed effects.

²³ Specifically, these estimates are robust to any time-invariant county differences (owing to county fixed effects), any economic time-varying differences in economic conditions within state or any state-level annual changes such as gubernatorial elections or fiscal policies (owing to $Pair \times Year$ fixed effects), changes in ratings (owing to $Rating \times Agency$ fixed effects), and any contemporaneous changes in nationwide economic variables such as policy interest rates or surprise election results in 2016 presidential election (owing to the DD estimation).

these had been manufactured the longest, used the most, and had been phased out in the U.S. since around 2008. We leverage this information by repeating the above regressions for the sample of counties contaminated with only these two chemicals and the bordering counties uncontaminated with any of the six PFAS. In columns (4) and (5) of Table IV, we see that estimating the effect on this alternative sample yields the same results.

It is important to gauge the economic magnitude of a 13 bps rise in offering yields. It is equivalent to the change in yield that would occur if the S&P credit rating of a typical municipal bond in the pre-event sample were to drop by three notches, from AAA to BBB. Alternatively, the estimated change is equivalent to a 6.2% increase in yield over the average offering yields in the pre-event sample. This increase in the offering yields is also similar to the increase of 16.7 bps caused by the opioid crisis estimated in (K. R. Cornaggia et al., 2021), 5 to 11 bps caused by newspaper closures in the county (Gao et al., 2020), and 16 bps for long-term bonds caused by one percent higher climate risk (Painter, 2020); and is significantly larger than the increase of 2 to 3 bps caused by state's fiscal policy for distressed municipalities (Gao et al., 2019).

When offering yields are elevated, municipalities may strategically adjust their bond-raising activities to balance overall borrowing costs with their capital needs. This requires weighing the higher costs of borrowing against the urgency of securing funds to address the newly discovered contamination and to maintain other expenditures. Consequently, it is unclear whether the total bond issuance amount would increase or decrease following the event. To investigate this, we aggregate the bond issuance amounts at the county-year level and analyze the changes using the same DD specification, incorporating *County* and *Pair*×*Year* fixed effects. Table V presents the results. Columns (1) through (3) indicate that neither the total borrowing amount nor the number of distinct bonds (at the CUSIP level) issued changed significantly.

[Insert Table V about here]

Noting further that remediating and preventing the contamination requires infrastructural upgrades, which would require long-term capital, we also examine compo-

sitional changes in the maturity of borrowing using a third difference specification. Here we interact the DD variable with an indicator for long-term borrowing, defined as bonds with maturity of 15 years and longer. We see in columns (4) to (6) that affected municipalities significantly tilted their borrowing towards long-term borrowing relative to control municipalities. More specifically, long-term borrowing amount increased by 24.5% ($[e^{0.219} - 1] \times 100$). Allowing for the assumption that maturity composition would have remained the same in the absence of the contamination discovery, we can infer the amount municipalities raised to address the contamination. Given the average annual long-term issuance of \$101 million per county, our results imply that infrastructure requirements to address contamination is nearly \$25 million, an amount roughly sufficient to build four new elementary schools ([J. Cornaggia et al., 2018](#), footnote 25).

3.2 Role of Credit Risk in Higher Offering Yields to Maturity

We next proceed to understand the reasons for the increase in yields. Our hypothesis is that the increase in offering yields reflects bond market's view on the increased credit risk of the municipalities from the affected counties. It is contributed by two factors. The first is an unexpected increase in expenditure for clean up and abatement technologies (see footnote 5 for an anecdotal example). Second, the expected future municipal revenues decline due to worsening economic outcomes, which we identify as elevated levels of out-migration, firm closures, and unemployment risk. We also document a decline in general public expenditure, which compounds the worsening effect through fiscal multiplier effect ([Dagostino, 2018](#); [Adelino et al., 2017](#)). Since municipalities are expected to balance their operating budgets ([Ang et al., 2017](#); [Haughwout et al., 2021](#)), the reduced revenues likely increases their credit risk, which is reflected in higher offering yields ([Goldsmith-Pinkham et al., 2023](#)).

We employ two strategies to analyze how municipal credit risk evolved following the contamination event. First, we examine changes in the credit ratings assigned to new bonds. We follow the same DD framework in equation 5, but replace

the $Rating \times Agency_i$ fixed effects with $Agency_i$ fixed effects to estimate within-agency changes in ratings. Consistent with [K. R. Cornaggia et al. \(2021, p. 11\)](#), we focus exclusively on general obligation (GO) bonds for this analysis, as the credit risk of non-GO (revenue) bonds depends on the specific underlying projects, for which detailed characteristics are unavailable.

Our second strategy involves analyzing the heterogeneity in the increase in offering yields based on municipal market characteristics that the literature associates with credit risk ([K. R. Cornaggia et al., 2021](#); [K. Cornaggia et al., 2022](#); [Gao et al., 2020](#)). We utilize these characteristics (\mathbf{X}) in a triple difference (DDD) specification of the following general form:

$$\begin{aligned} YTM_{imcpt} = & \alpha_0 + \beta_1 Treatment_c \times Post_t \times \mathbf{X} + \beta_2 Treatment_c \times Post_t \\ & + \beta_3 Treatment_c \times \mathbf{X} + \beta_4 Post_t \times \mathbf{X} + \beta_5 \mathbf{X} + \text{Bond and County Controls} \quad (6) \\ & + Capital_i + Rating \times Agency_i + \alpha_c + \gamma_{pt} + \epsilon_{imcpt}. \end{aligned}$$

Here \mathbf{X} represents the third-difference binary variable that proxies for municipal credit risk. The idea is that the offering yields will see a larger increase for the characteristics associated with a higher risk. The coefficient β_1 captures this differential effect. In addition to shedding light on the credit risk mechanism, these DDD estimations also reaffirm the causal interpretation of the results in the sense that the identifying assumption for this estimator is weak: it requires that there be no contemporaneous shock that affects the relative difference across the subgroups (formed by the third difference variable) within the treated group in the same manner as the contamination does. We use three different variables for the third difference, each associated with credit risk.

The first variable reflects the credit risk associated with the type of cash flows that would be used to pay the coupons and face value amounts. General obligation (G.O.) municipal bonds are backed by the cash flows derived from taxation power of the municipalities and carry lower credit risk than other bonds. Thus the effect of the event should be less pronounced for G.O. bonds than for non-G.O. bonds. Consistent with

this, the estimate in column (2) of Table (VI) shows that the increase in the offering yields of the treated non-G.O. bonds was 16 bps larger than the treated G.O. bonds, adjusting for the contemporaneous changes in the yields experienced by the unaffected municipalities.

[Insert Table VI Here]

The second variable reflects the credit risk associated with state assistance policies for financially distressed municipalities, which influence creditor protections and local credit risk (Gao et al., 2019). The authors argue that nine states (ME, MI, NC, NJ, NY, OH, PA, NV, and RI) have proactive policies to assist distressed municipalities. Hence creditor's view municipalities from these states as having less credit risk (and also default risk) than rest of the states. We conjecture that the municipalities in non-proactive states (all states other than the nine proactive states) will see a higher increase in the offering yields after the contamination discovery relative to those from the proactive states. Consistent with the prediction, the estimate in column (3) suggests that the offering yields of affected municipalities located in non-proactive states rose on average 13 bps more than the affected municipalities in the proactive states, while adjusting for the contemporaneous changes in the yields experienced by the unaffected municipalities.

The third variable we examine is the count of PFAS chemicals with which the drinking water of a county was contaminated with. This variable is not directly associated with credit risk, but with the expected revenue needs of the affected municipalities. Different PFAS chemicals require specific different treatment techniques, hence counties contaminated with more PFAS chemicals would require more investment in the infrastructure.²⁴ Hence, we classify counties where all six contaminants

²⁴ We 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 treatment and abatement technology to prevent future contamination are proportional to the contamination levels. However, as previously noted in Footnote (1), such technology were largely unavailable at the time of the event, and any remediation effort required a substantial fixed cost, regardless of the contamination intensity. Consequently, it is likely that the expected needs to address the contamination depends to a large degree on how many contaminants were detected.

were found into high contamination group and the of the affected counties to low contamination group. The estimate in column (4) of Table VI suggests that relative to the contaminated counties with fewer chemicals, the offering yields of the affected municipalities from the more number of detected chemicals experienced an increase of 23 bps, adjusting for the contemporaneous changes in the yields experienced by the unaffected municipalities.

To summarize, credit risk of the affected bonds on average increased after the event, reflected in changes in their credit ratings. Furthermore, the findings utilizing triple difference specification reaffirm that within the affected municipalities, the offering yields increased more for the bonds having characteristics associated with higher credit risk, indicating that municipal investors likely recognized that credit risk increased after the event.

3.3 Role of Capital Supply in Higher Offering Yields to Maturities

Thus far, we have documented that offering yields increased after the event, likely driven by heightened municipal credit risk. On the capital demand side, while there was no significant rise in overall borrowing amounts, long-term borrowing among treated municipalities increased by nearly 25%. Although our empirical framework cannot fully disentangle supply and demand shifts, an outward shift in the demand curve alone cannot account for the observed rise in yields (price) alongside the lack of a significant increase in total borrowing (quantity). To explore potential capital supply shifts, we focus on two important classes of investors in municipal markets: mutual funds and households. We argue that if credit supply constraints contributed to the higher yields, treatment effects would vary across areas based on differences in the characteristics of municipal capital suppliers. We conduct two analyses to investigate this. First, we examine portfolio changes in mutual fund holdings of bonds issued by affected versus unaffected municipalities. Second, we exploit variation in county-level socio-economic characteristics, which influence the willingness and incentives of

household investors to supply municipal capital, and assess heterogeneous treatment effects using the triple difference specification.

3.3.A Change in Capital Supply by Mutual Funds

In the corporate bond market, institutional demand and variations in investment mandates significantly influence bond pricing (Bretscher, Schmid, Sen, and Sharma, 2022). Similarly, mutual funds play a pivotal role in the municipal bond market, with their holding accounting for about 30% of the total outstanding municipal bonds (Y. Li et al., 2023) and their portfolio allocation decisions influencing both the issuance and pricing of municipal bonds (Y. Li et al., 2023; Adelino et al., 2023). Unlike households, mutual funds are sophisticated investors and are more likely to base their capital allocation on fundamental municipal characteristics, such as credit risk, rather than household sentiment, which is prone to overreacting to events like contamination discovery.

To isolate the decisions of mutual funds regarding their exposure to affected municipalities, we examine the holdings of the same municipal issuer both before and after the event. So we focus exclusively on bonds issued by all municipalities in our sample prior to 2013, the start of our sample period. This approach is not feasible for newly issued bonds. We begin by extracting the first six characters of the CUSIP codes for new bonds included in our main sample to identify relevant municipalities. Using this identifier, we merge these records with bond holdings data from the CRSP Mutual Fund database and exclude newly issued bonds (identified by their full eight-character CUSIP) from the merged dataset. This process yields a panel dataset at the *fund*×*CUSIP8*×*year-quarter* level. Among bonds issued before 2013, we classify those from municipalities in contaminated counties as *Affected* and those from control counties as *Control*. We focus specifically on holdings in terms of number of bonds, instead of market value of bonds, because the market value of bonds may decline also due to repricing of the bonds, even when the funds do not reduce their holdings. We regress the number of bonds i (at CUSIP 8 level) held by mutual fund f bond in year-

quarter q using the following specification:

$$Y_{ifq} = \beta_0 + \beta_1 \text{ Affected Bond}_i \times \text{Post}_q + \gamma \text{ Controls} + \alpha_i + \delta_f + \lambda_q + \epsilon_{ifq}. \quad (7)$$

This specification includes bond (eight-character CUSIP), fund, and year-quarter fixed effects, controlling for time-invariant characteristics of funds, and bonds (hence, also of the municipality) as well as common quarterly shocks. The coefficient of interest, β_1 , captures the change in holdings of the same bond by the same fund before and after the event for *Affected bonds* relative to *Control bonds*. Control variables include management fees (as a percentage of average net assets), expense ratios, and the natural logarithm of one-quarter lagged values of the total net assets of the fund and market value of the underlying bonds.

[Insert Table VII about here]

Table VII presents the results from regressing natural log of the number of bonds held by funds. The estimate in column (1) indicates that bond holdings decreased by 1.3% across all funds, with reductions of 1.4% for retail funds and 1.2% for institutional funds. In contrast, the reduction was not statistically significant for index funds and ETFs, which typically track benchmarks. This variation in response across fund types supports the interpretation that active funds reduced their exposure to previously issued bonds of affected municipalities relative to the unaffected ones. For robustness, we regressed the number of bonds (instead of their natural log) using PPML regression and find similar results and report the results in Table IA.I in Online Appendix.

Although the reduction in holdings cannot be directly measured for newly issued bonds, we argue that it is plausible that this reduction in capital supply effect extended to them as well. This is especially because new bond pricing is particularly sensitive to mutual fund allocation decisions, given that the funds typically invest early in new municipal bonds and gradually sell their stakes to other investors in the secondary market (Azarmsa, 2021). These findings suggest that a reduction in capital supply contributed to the increase in offering yields for the affected municipalities.

3.3.B Role of Socio-Economic Characteristics in Capital Supply

We next examine the role of household investors in supplying capital to the municipal bond market. According to the Federal Reserve’s 2018 Flow of Funds data, households directly held approximately half of all outstanding municipal bonds between 2002 and 2018, indicating that they are an important investor class in this market. Assuming that the capital demand function do not systematically differ across counties with different investor clientele ([K. R. Cornaggia et al., 2021](#)), significant heterogeneity in offering yields across such counties would suggest that household capital supply influences municipal bond pricing.

The differences in investor clientele we examine are linked to the nonpecuniary utility households derive from supplying capital to local municipalities, which are responsible for last-mile delivery of public goods. To identify these clientele differences, we utilize three socio-economic measures.

The first measure is the homeownership rate. Homeownership creates mobility constraints and incentivizes residents to invest in their local communities and amenities, thereby strengthening social capital ([DiPasquale and Glaeser, 1999](#)). Homeowners derive additional nonpecuniary benefits from supporting their local communities, which increases their willingness to provide capital to local municipalities. Moreover, [Babina, Jotikasthira, Lundblad, and Ramadorai \(2021\)](#) show that the tax advantages associated with in-state municipal bonds predict higher ownership by in-state investors. Their measure of tax advantage, privilege, accounts for both high state income tax rates and exemption of taxes for in-state bonds. Extending this tax-advantage incentives of in-state investors to households, and in line with [K. R. Cornaggia et al. \(2021\)](#), we argue that the incentivizing effect of homeownership on investing in local municipal bonds is amplified in states with higher tax privilege. Consequently, we conjecture that in states where the tax privilege exceeds the sample mean, counties with higher ex ante homeownership rate should experience lower increase in offering yields after the contamination discovery. As mentioned earlier,

we construct county-level homeownership rate as the fraction of total returns in IRS that have mortgage deductions.

Our second and third measures relate to social capital, which captures the extent to which individuals perceive themselves embedded in their communities (Chetty et al., 2022b, 2022a). These measures are derived from the structure of social networks in the U.S. The specific dimension of social capital we examine is local social cohesiveness, which facilitates collective action and fosters pro-social behavior and investments by enforcing social norms and sanctioning deviations. The two metrics we employ to measure social cohesiveness are support ratio and clustering. Support ratio is the rate at which pairs of friends in a community have other friends in common. Clustering is the rate at which two friends of a given individual are in turn friends with each other. Consistent with our conjecture regarding homeownership rate, we hypothesize that counties with higher levels of social capital are better equipped to mitigate the adverse effects of contamination discovery on offering yields.

We utilize the above three socio-economic measures in a triple difference specification by categorizing sample counties into high and low groups using the cross-sectional median values. For homeownership rate, the classification is based on 2015 data, while for the two social capital measures, which are cross-sectional, the classification is independent of a specific year. We then regress offering yields using the triple difference specification from equation (6) and present the results in Table VIII. Columns (1) to (3) indicate that, among affected counties, the increase in offering yields was less by 19, 15, and 17 bps, respectively, in counties with ex ante high homeownership rates and high social cohesion, measured by high support ratio and high clustering. These findings highlight the role of households' stakes in their local areas in sustaining the supply of municipal capital after the contamination discovery and mitigating the impact on offering yields.

[Insert Table VIII Here]

Overall, capital supply by both mutual funds and households shaped the rise in offering yields after the contamination discovery in a manner consistent with their expertise and incentives.

4 Broader Economic Effects of PFAS Contamination Discovery

Section 3 reported the effects of PFAS contamination discovery on municipal finances. While conceptually aligned with the findings and arguments of [K. R. Cornaggia et al. \(2021\)](#) regarding the U.S. opioid crisis, our results from the previous section are novel because of the unique significance of PFAS contamination elaborated in footnotes 1, 2, 10, and 11. This section broadens the analysis to investigate a wider range of real economic outcomes, offering a novel contribution beyond what can be inferred by synthesizing results from existing work.

We begin by examining changes in public spending—municipal revenues, taxes, expenditures, and public employment—following contamination discovery. [Adelino et al. \(2017\)](#) document that these play a role in local economic growth, especially through fiscal multiplier effects. Unlike [Adelino et al. \(2017\)](#), who focus on increase in public expenditure and employment following credit rating upgrades that enhanced municipal borrowing capacity, we examine the reductions in these quantities. Additionally, we quantify shifts in population out-migration, firm dynamics, and unemployment risks, capturing the broader economic repercussions of PFAS contamination. These findings resonate with the anecdotal example at the start of this article, where a Maine farmer’s century-old business was forced to close after PFAS contamination was discovered.

4.1 Effects on Municipal Operations

We examine changes in municipal revenues and expenses after the contamination discovery to understand whether they were also affected in the real economy. We aggregate revenues and expenditures to county-year level for all municipalities at county level and below (identified by type code 1 to 5) from the Government Finance

data of [Pierson et al. \(2015\)](#). The regression specification is as follows:

$$Y_{cpt} = \alpha_0 + \beta_1 \text{Treatment}_c \times \text{Post}_t + \text{County Controls} + \alpha_c + \gamma_{pt} + \epsilon_{cpt}, \quad (8)$$

where county c of pair p in year t experiences outcome Y . Subscript p in Y_{cpt} and γ_{pt} denotes that counties may be repeated for all county pairs they are part of. Post_t takes the value of 1 for $t \geq 2016$ and 0 otherwise. α_c and γ_{pt} denote county and $\text{Pair} \times \text{Year}$ fixed effects, respectively, serving the same purpose as in equation (5). Control variables are also identical to those used in that equation. Standard errors are clustered by county. The outcome variables of interest include the natural logarithm of revenues, total taxes, and property taxes as sources of cash flows, as well as general expenditures and general current expenditures as uses of cash flows.²⁵

[Insert Table IX about here]

The regression results are reported in Table IX. The findings indicate that all three sources of cash flows—revenues, total taxes, and property taxes—declined in the contaminated counties by 3.8%, 5.3%, and 4.3%, respectively, relative to the control counties. Moreover, municipalities reduced both general and general current expenditures by approximately 3%. This decline is approximately in the middle of the range of estimates for the rise in expenditure associated with the municipal rating upgrades during Moody’s 2010 rating recalibration and more than six times the expenditure increase associated with one-standard-deviation increase in fraction of local municipalities experiencing rating upgrade ([Adelino et al., 2017](#), p. 3245).

Note that these estimates account for contemporaneous county population, suggesting that the expenditure reductions exceeded what could be attributed solely to changes in resident population. We infer that these expenditure cuts likely reflect a dual response to diminished revenues and increased borrowing costs in the primary

²⁵ The corresponding variables in [Pierson et al. \(2015\)](#) are: revenues (*Total_Rev_Own_Sources*), total taxes (*Total_Taxes*), property taxes (*Property_Tax*), general expenditure (*General_Expenditure*) and general current expenditure (*General_Current_Expend*). They define construction of these variables from census data codes in Appendix B of their paper. Expenditure relates to external payments of a government and excludes amounts transferred to funds or agencies of the same government. Broadly speaking, general expenditure includes expenditure, construction-related expenses, and capital outlay, except interest payments for all activities excluding utilities. General current expenditure is used to pay employees, purchase supplies and hire contractors.

market. Such reductions in public spending can have adverse implications for the local economy, potentially degrading the quality of public goods and creating negative spillovers in the private sector due to the fiscal multiplier effect (Yi, 2020; Adelino et al., 2017; Dagostino, 2018).

4.2 Effects on Public Employment

Since one important use of municipal funds is to maintain (or enhance) the directly-hired employees of local governments, we next examine changes in public employment. More precisely, we look at the effects on full-time-equivalent public employment. We regress the natural log of public employment, share of public employment among total employment, and public employment per 1000 population using the specification in equation (8).

[Insert Table X about here]

Table X shows the regression results. Columns (1) through (3) indicate that, relative to control counties, the contaminated counties experienced a 12% decline in full-time-equivalent public employment, a 1 percentage point reduction in the share of public employment, and a decrease of 1.8 public jobs per 1,000 population. Recall that these estimates account for contemporaneous county population, indicating that the reduction in employment exceeded what could be attributed solely to changes in resident population. The magnitude of these cuts is substantial, comparable to the employment reductions reported in municipalities with stressed insurers (Amornsiripanitch, 2022), and two to four times larger than the public employment increases associated with credit rating upgrades (Adelino et al., 2017, p. 3249).

We further investigate whether municipalities in more financially distressed areas reduce employment to a greater extent. To do so, we classify counties into high and low interest burden groups based on the ratio of total interest payments to total revenues in the pre-event year, 2015. These ratios are aggregated across all municipalities and county-level governments (identified by type codes 1 to 5) using data from the Government Finance dataset of Pierson et al. (2015). The estimates presented in

columns (4) through (6) suggest that municipalities in counties with higher pre-event financial distress indeed tend to reduce public employment more significantly. However, statistical significance is only observed at the 10% level for the first two outcome variables, and the effect is not significant for the third.

We argue that contamination discovery drives both the tightening of financial constraints—manifested as higher borrowing costs—and declining revenues, which are linked to deteriorating real economic outcomes such as population out-migration and weakened firm dynamics (both examined in subsequent sections). These pressures compel municipalities to reduce spending on public employment and other expenditures. This mechanism is distinct and diverges from the financing constraints channel of [Adelino et al. \(2017\)](#), where increase in public spending is solely driven by relaxation of financial constraints following municipal credit rating upgrades. While the spending cuts are likely driven by both higher borrowing costs and declining revenues, our empirical framework is unable to disentangle their relative contributions.

4.3 Effects on Population Out-migration

A central implication of Tiebout’s seminal model of spatial sorting is that individuals would sort across local communities to align with their preferences for public goods ([Tiebout, 1956](#)). The extent of the sorting (migration) is influenced by mobility costs, which may vary across populations and regions ([Rhode and Strumpf, 2003](#)). Following the discovery of PFAS contamination, population out-migration from affected counties is likely, particularly among higher-income individuals who face lower mobility costs and over smaller geographic areas such as neighboring counties, as migration across neighboring counties is less costly than across states. Increased out-migration reduces the taxable base and revenue sources for local municipalities, likely contributing to the revenue declines estimated earlier ([Hastie, 1972](#); [J. Cornaggia et al., 2019](#); [Yi, 2020](#)). To explore this dynamic, we examine changes in within state out-migration from the affected counties following the contamination discovery.

We measure out-migration using the IRS SOI county-to-county migration dataset, focusing exclusively on within-state migration. Our first measure is the natural logarithm of the number of individuals migrating out of a county to any other county within the same state. The second measure is the net out-migration rate, calculated as the outflow of individuals from a focal county to other same-state counties minus the inflow from other same-state counties to the focal county, scaled by the focal county's population and expressed as a percentage. The third measure is the ratio of out-migrating individuals to in-migrating individuals. Additionally, the fourth and fifth measures capture the county-aggregated adjusted gross income (AGI) of in-migrating and out-migrating individuals, respectively, both scaled as a percentage of the total AGI of county residents. The regression specification is from equation (8) and includes the same control variables.

[Insert Table [XI](#) about here]

Table [XI](#) presents the regression results. Column (1) shows that, relative to the control counties, the affected counties experienced 2.4% higher out-migration to the same-state counties after the discovery of PFAS contamination, adjusted for the in-migration from those counties. This increase is significant, almost 26% larger than the rise in in-migration of 1.9% observed after municipal credit rating upgrades ([J. Cornaggia et al., 2019](#), p. 17). Column (2) indicates that net out-migration per resident individual increased by 1 percentage point in affected counties relative to controls, while column (3) shows a 2.4 percentage point rise in the out-migration rate per in-migrating individual. Furthermore, columns (4) and (5) reveal that the wealth of in-migrating individuals as a percentage of that of residents declined by 0.15 percentage points in contaminated counties, whereas the wealth of out-migrating individuals remained unchanged. Together, these findings suggest that while the wealth profile of out-migrants matched that of residents, in-migrants had lower wealth, resulting in an overall reduction in the aggregate taxable personal wealth. In summary, PFAS contamination discovery not only resulted in out-migration to other same-state counties but also lowered the overall taxable wealth of contaminated counties because

the aggregate wealth of in-migrating population was insufficient to compensate for the wealth lost to out-migration.

4.4 Effects on Wage and Firm Dynamics

Seminal works on the theory of equalizing differences suggests that workers require a wage premium (compensating wage differentials) to accept jobs with undesirable nonwage characteristics, such as higher risks of mortality or injury in hazardous occupations ([Rosen, 1974](#); [Thaler and Rosen, 1976](#); [Brown, 1980](#); [Rosen, 1986](#), among others). The discovery of PFAS contamination introduces a new health risk associated with living and working in the affected counties, likely prompting workers to demand higher compensating wage differentials. This effect is expected to be particularly pronounced in tradable industries, where skilled workers face lower mobility costs and can relocate more easily. Consequently, firms in tradable sectors may face increased labor costs, leading to higher rates of firm closures compared to nontradable industries. This prediction—that higher compensating wage differential makes tradable industries more susceptible to a local contamination shock than nontradable industries—is novel. Existing literature has predominantly documented the higher sensitivity of nontradable employment to changes in local demand shocks, such as those caused by declining housing prices ([Mian and Sufi, 2014](#); [Giroud and Mueller, 2017](#)), rising stock market wealth ([Chodorow-Reich, Nenov, and Simsek, 2021](#)), or reduced demand following local corporate bankruptcies ([Bernstein, Colonnelli, Giroud, and Iverson, 2019](#)). By contrast, we highlight a unique supply side mechanism where increased labor costs in tradable industries due to compensating wage differential, rather than local demand fluctuations, drive differential impacts on firm dynamics across the two industries.

We investigate changes in wages, firm closures, and job creation using data from the Census Bureau’s Business Dynamics Statistics. More specifically, we look at the natural log of the average payroll per employment, the number of firm deaths and establishment death, as well as job creation and destruction. In terms of data, we

construct a *Pair*×*Industry Type*×*Year* level panel dataset, where industry type (tradable or nontradable) is defined at the 4-digit NAICS level following (Mian and Sufi, 2014). We employ the following triple difference specification:

$$\begin{aligned}
Y_{c ipt} = & \alpha_0 + \beta_1 \text{Treatment}_c \times \text{Post}_t \times \text{Tradable}_i + \beta_2 \text{Treatment}_c \times \text{Post}_t \\
& + \beta_3 \text{Treatment}_c \times \text{Tradable}_i + \beta_4 \text{Post}_t \times \text{Tradable}_i + \beta_5 \text{Tradable}_i \\
& + \text{County Controls} + \alpha_c + \gamma_{pt} + \epsilon_{c ipt}.
\end{aligned} \tag{9}$$

Here, *Tradable_i* is a binary indicator equal to 1 for tradable industries. Subscript *p* in *Y_{c ipt}* and *γ_{pt}* denotes that counties may be repeated for all county pairs they are part of. County controls and fixed effects are the same as in equation (8).

[Insert Table XII about here]

Table XII shows the results of the above regression. Column (1) shows that, within affected counties, payroll per employee in the tradable sector increased by 5% relative to the nontradable sector, while accounting for contemporaneous trends in the two sectors in the control counties. This finding aligns with the expected rise in compensating wage differentials following the contamination discovery. Similarly, columns (2) and (3) indicate that the number of firm and establishment deaths increased respectively by 4% and 4.2%. Finally, columns (4) and (5) show that job creation fell by 7.3%, while job destruction did not, indicating that overall employment decreased in tradable industries relative to the nontradable, while adjusting for similar changes in control counties.

These results collectively highlight the negative impact of contamination discovery on wages, firm dynamics, and employment in the private sector, particularly within tradable industries.

4.5 Effects on Self-Employment

Self-employment can be broadly classified into two contrasting forms. The first is entrepreneurial self-employment, characterized by individuals who undertake risky ventures, innovate by introducing new goods, services, or production processes, and

exhibit traits such as high confidence, substantial human capital, and the ability to earn significant returns on their unique skills (Kihlstrom and Laffont, 1979; Gennaioli, La Porta, Lopez-de Silanes, and Shleifer, 2013; Murphy, Shleifer, and Vishny, 1991). In contrast, disadvantaged self-employment arises from necessity rather than opportunity, often involving individuals with lower productivity. A significant portion of the self-employed have been estimated to be one-person retail business owners who transition to self-employment after losing salaried jobs (Evans and Leighton, 1989), and only a small fraction of the self-employed actively seek to grow their businesses (Pugsley and Hurst, 2011). Glaeser (2009) articulates the disparity between these two forms of self-employment by noting that despite their vastly different economic roles and trajectories, both Michael Bloomberg and a hotdog vendor outside city hall are technically self-employed.

We investigate changes in self-employment dynamics following the discovery of contamination. Given the worsening of a broad range of real economic outcomes associated with the event, we hypothesize that contaminated counties would experience an increased transition into self-employment, driven by heightened unemployment risk (Hou et al., 2025). Our primary measure of self-employment is the natural logarithm of the number of nonemployer businesses, derived from the Census Bureau’s Nonemployer Statistics dataset. Nonemployer businesses are defined as those with no paid employees, annual receipts of \$1,000 or more (\$1 or more in the Construction industry), and subject to federal income taxes. This measure is well-suited to capturing the disadvantaged form of self-employment. To complement this measure, we employ a second measure of self-employment based on the natural logarithm of the number of tax returns (a proxy for households) reporting self-employment tax, as recorded in the IRS tax returns dataset (variable N09400), aggregated at the county level. Our third measure is the percentage of total tax returns filed in a county that report self-employment tax.

[Insert Table XIII about here]

We estimate the effects on the three self-employment measures using the specification in equation (8) and report the result in Table XIII. The estimates in columns (1) through (3) indicate that, compared to the control counties, the affected counties experienced a 1% increase in the number of nonemployer businesses and self-employed households, along with a 0.13 percentage points rise in the share of households reporting self-employment income. Collectively, these results align with the idea that the contamination discovery likely compelled some individuals and households to transition into disadvantaged self-employment in line with (Evans and Leighton, 1989; Pugsley and Hurst, 2011), likely due to elevated unemployment risk Hou et al. (2025).

5 Supplementary Discussion

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

5.1 Health-related Outcomes

Given that PFAS contamination broadly relates to health risk, in this section we examine two sets of trends, one related to changes in health insurance coverage after the revelation of the contamination and second related to the differences in long-term trends in the contaminated and control counties.

5.1.A Effect on Household Health Insurance Coverage

We utilize one-year ACS survey data to examine changes in health insurance coverage following the event. Using a difference-in-differences (DD) specification, we regress the percentage of households in a county reporting health insurance coverage, including both any form of health insurance and private health insurance. The results are presented in panel A of Table XIV. As shown in columns (1) and (2), the proportion of households in contaminated counties enrolled in any health insurance plan and in a private plan increased by 0.387 and 0.362 percentage points respectively relative to the neighboring uncontaminated counties. These findings are not only consistent with

the general population becoming aware of the PFAS contamination and its perceived health effects but also in line with the trends of increased out-migration and higher compensating wage differentials discussed earlier.

5.1.B Long-Term Difference in PFAS-related Health Conditions

As noted earlier, although the contamination was discovered in 2016, the exact timing and method of contamination in the drinking water systems of these counties remain unknown. If the contamination had persisted for a prolonged period, health outcomes in the affected counties could be worse than those in control counties. While the precise medical mechanisms linking PFAS exposure to health effects are still under investigation, existing studies have shown associations between PFAS exposure and kidney cancer ([Shearer et al., 2021](#); [NIH, 2020](#)), pregnancy complications such as preeclampsia, and congenital anomalies like heart defects ([Szilagyi, Avula, and Fry, 2020](#); [Ou et al., 2021](#)). If the population in the contaminated counties was exposed to elevated PFAS levels over a longer period, their health outcomes may be worse on average. Therefore, we examine long-term health outcomes between treated and control counties, using available data. Specifically, we analyze county-level kidney cancer mortality rates from 1999 to 2016 (CDC Wonder) and natality outcomes of eclampsia and congenital anomalies from 1990 to 2002 (Division of Vital Statistics, National Center for Health Statistics).²⁶

Panel B of Table [XIV](#) presents the results. Columns (1) to (3) show that, relative to the control counties, the contaminated counties had 0.332 more deaths from kidney cancer per 100,000 population, a 0.05 percentage point higher incidence of eclampsia among singleton births, and 0.014 more congenital anomalies (among newborns reported to have such anomalies). These findings suggest higher PFAS exposure, but they should be interpreted with caution. Numerous other factors may contribute to

²⁶ Note that since the natality data files record eclampsia, but not preeclampsia, we examine eclampsia, while the studies referenced earlier show association between PFAS exposure and preeclampsia. Both the conditions are pregnancy-related complications characterized by high blood pressure, though eclampsia also involves seizures.

these trends, and we did not find significant differences in other conditions typically associated with PFAS exposure, such as low birth weight.

5.2 Legal Liabilities as a Source of Economic Stress

Previously, we documented a deterioration in economic conditions following the discovery of contamination, including increased net out-migration, the in-migration of lower-income populations, and declines in per capita public expenditures and employment. In this section, we highlight another potential challenge for municipal issuers and local governments: growing legal liabilities. Although we do not attempt to quantify this impact, legal actions against municipalities, water utilities, and counties are a significant factor to consider. For instance, after the 2016 contamination discovery, Tennessee Riverkeeper Inc. filed a federal lawsuit under the Resource Conservation and Recovery Act of 1976 against BFI Waste Systems (a municipal entity in Decatur, Alabama), the City of Decatur, Morgan County, and 3M for the dumping of PFOS and PFOA chemicals into the Tennessee River and surrounding landfills ([The Decatur Daily \(Alabama\), June 25, 2016](#)). Notably, Morgan County is among the contaminated counties in our sample.

In addition to localized lawsuits, numerous legal actions and multidistrict litigations have been jointly filed by water systems, state attorneys, and local governments across the U.S. against PFAS manufacturers. As noted in Footnote (2), there are currently over 15,000 active PFAS-related claims, including significant multidistrict litigation involving 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](#)). Brunswick County, like Morgan County, is one of the contaminated counties included in our sample. These legal developments underscore the multifaceted challenges faced by municipalities, extending beyond economic disruptions to encompass complex and ongoing litigation risks.

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

Panel A of Figure III reveals that the increase in offering yields for municipal bonds from contaminated counties was pronounced for approximately three years before gradually diminishing. This raises the question: if the contamination event imposed genuine financial constraints on municipalities, why did the heightened yields not persist? Was the rise driven primarily by temporary factors, such as heightened market sentiment?

A purely behavioral explanation, such as sentiment, is inconsistent with several of our findings. First, real economic outcomes, such as increased out-migration, reduced public employment, and lower expenditures, deteriorated after the event. Second, mutual funds—typically more sophisticated and less influenced by sentiment than retail investors—reduced their allocations in bonds issued by affected municipalities. Third, numerous anecdotal accounts explicitly link contamination to budgetary provisions, legal challenges, and bond issuances aimed at funding cleanup efforts.

We conjecture that the gradual attenuation of the yield effect reflects heightened regulatory and legislative attention at both state and federal levels, which mitigated the financial risks for affected municipalities.²⁷

At the federal level, the 116th Congress introduced over 80 pieces of PFAS-related legislation ([National Conference of State Legislatures, Jan 25, 2021](#)). Additionally, numerous local regulatory initiatives have been proposed, with some successfully enacted ([PFAS Project Lab, 2023b](#)). These interventions likely alleviated the expected financial pressures on municipalities, thereby moderating the effect on bond yields over time. In April 2024, EPA has established maximum contaminant levels for PFOA,

²⁷ 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.

PFOS, PFHxS, PFNA, and GenX in drinking water, designated PFOA and PFOS as hazardous substances under CERCLA, and committed \$1 billion to aid states and territories address the contamination ([EPA, n.d.](#)).

6 Conclusion

This study demonstrates the cascading economic and financial consequences of PFAS contamination on local municipalities, firms, and employment. Using a paired-county difference-in-differences approach, we find that the 2016 revelation of PFAS contamination in the drinking water systems of 200 U.S. counties led to an increase in offering yields and credit risk of municipal bonds issued by municipalities in the contaminated counties relative to those in bordering uncontaminated counties. This increase was contributed by a reduction in capital supply by mutual funds.

Beyond municipal finances, the contamination discovery also negatively affected broader economic outcomes. Municipal revenues and tax collections declined, partly due to out-migration, which disproportionately involved higher-income individuals, further eroding the local taxable income base from which municipalities derive a significant portion of their revenues. Private businesses in tradable industries faced higher average payroll costs, consistent with compensating wage differentials, which contributed to increased firm closures and reduced job creation in these industries. Additionally, contaminated counties saw a rise in disadvantaged self-employment, reflecting heightened unemployment risks.

As legislative efforts to regulate PFAS and establish detection limits continue to progress in the U.S. ([PFAS Project Lab, 2023b](#)) and internationally ([WQA, n.d.](#)), these findings may aid crafting regulatory response.

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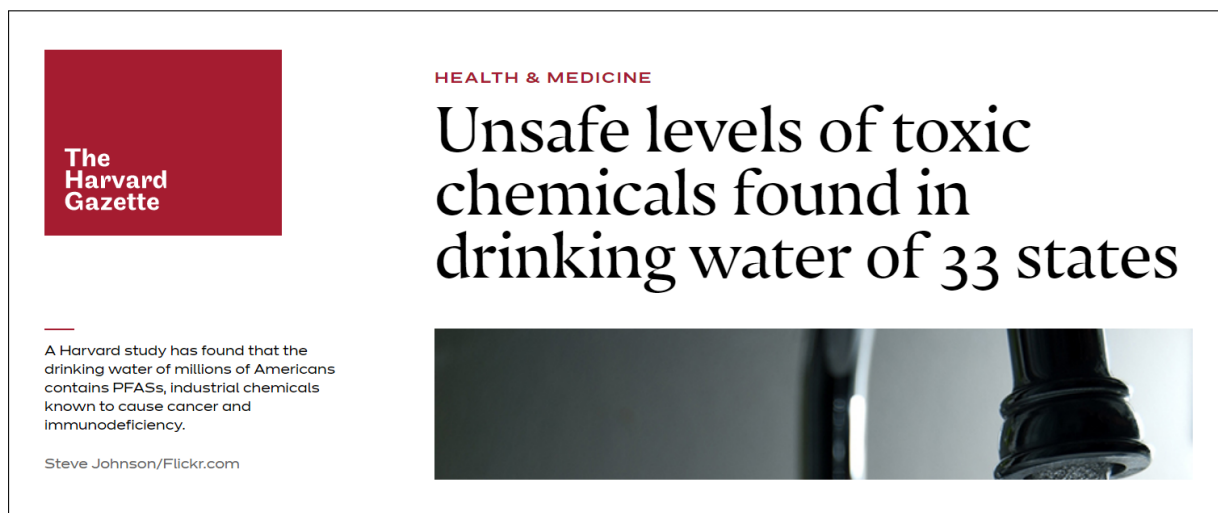
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Figure I: The Event

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”

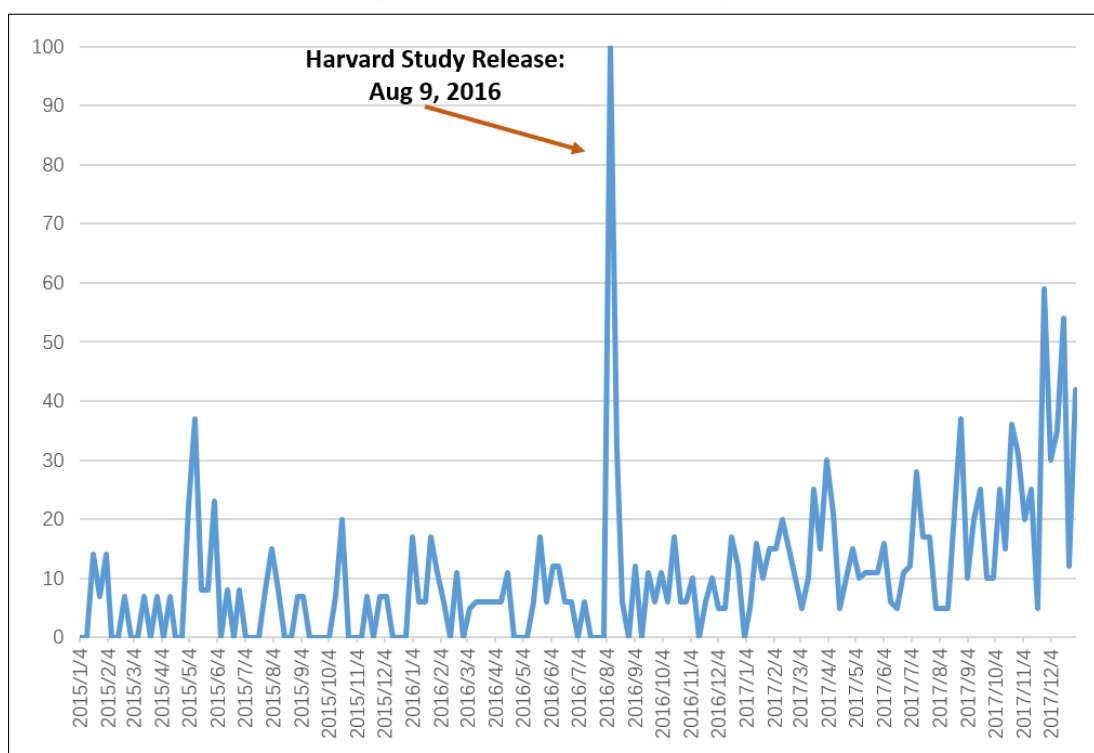


Figure II: Illustration of Treatment and Control Counties

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*).

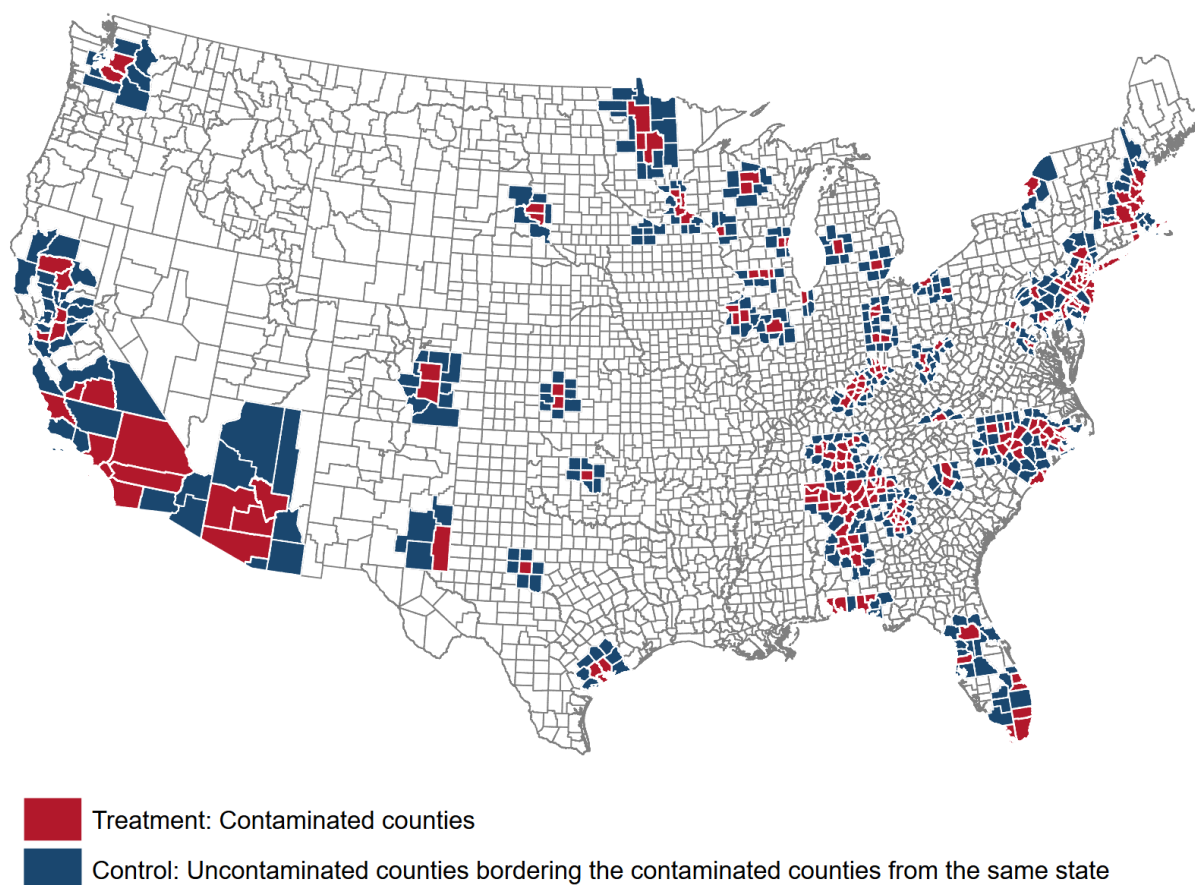


Figure III: Pre-Trends

Panel (A) plots the coefficients on β 's from regressing the offering yield to maturity (YTM) using the following specification in equation (2). Panel (B) through (D) of this figure plots the coefficients from regressing four *County* \times *Year*-level outcomes—share of PFAS industries, number of drinking water violation per million population, number of establishments (in natural log), and number of employment (in natural log) using the specification in equation (3):

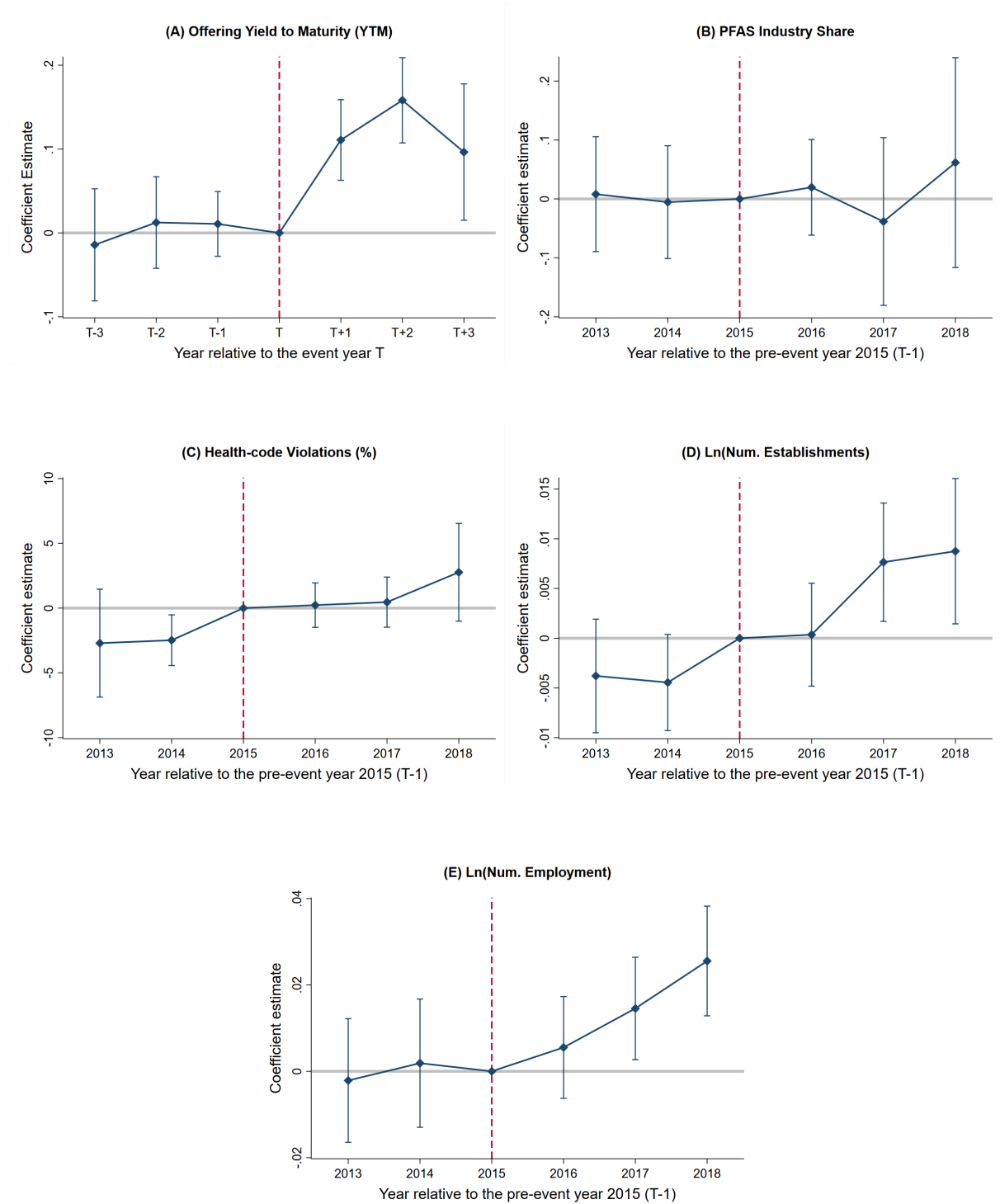
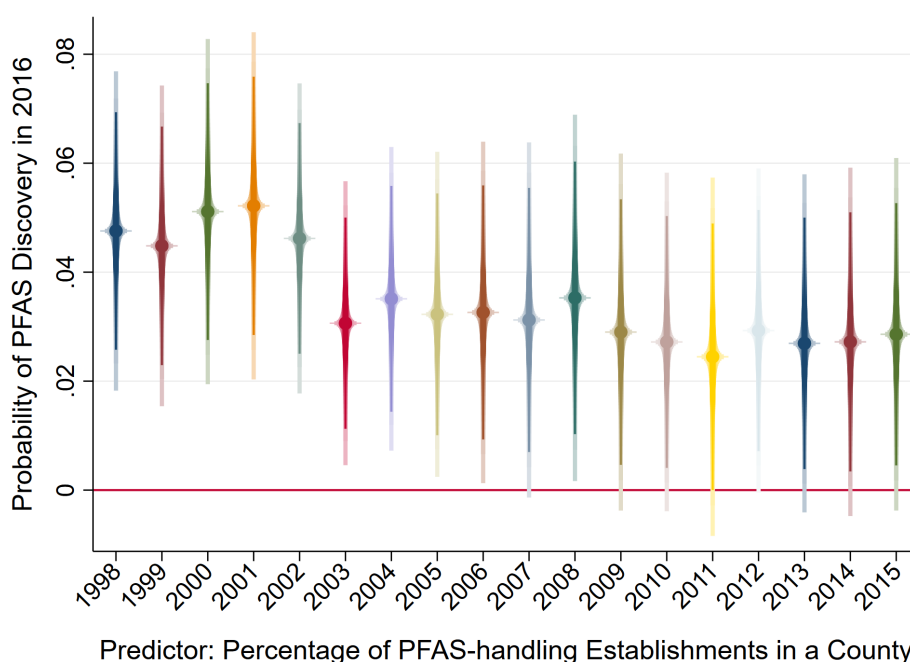


Figure IV: Predicting the 2016 Discovery of PFAS Contamination of Drinking Water

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 following specification in equation (4). 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 using the same specification. 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

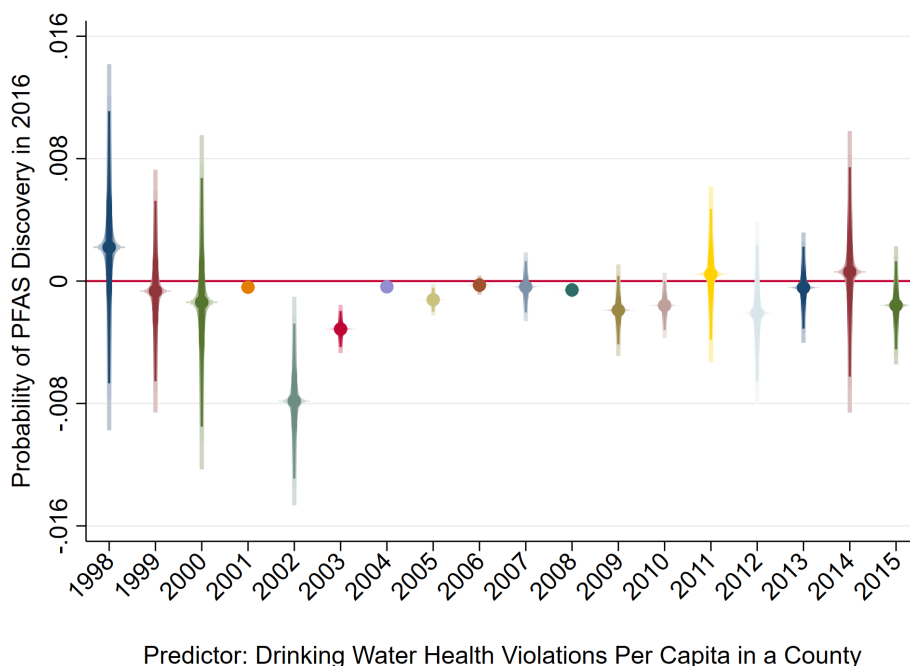


Table I: Major Developments Surrounding PFAS in the U.S.

This table summarizes major events related 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 \(2014\)](#).

<i>Before 2000</i>	
1940–1950	<ul style="list-style-type: none"> 3M invented PFOA DuPont purchased PFOA to produce Teflon
1999	<ul style="list-style-type: none"> Lawsuit brought against DuPont (Tennant v. E. I. du Pont de Nemours and Company)
2000	<ul style="list-style-type: none"> 3M ceased production of PFOA DuPont started to manufacture PFOA on its own
<i>2001–2010</i>	
2001	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> The EPA fined DuPont \$16.5 million
2009	<ul style="list-style-type: none"> The EPA set a provisional limit of 0.4 ppb for short-term exposure GenX, a short-chain PFAS, was introduced to replace PFOA
<i>2011–2024</i>	
2011	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> Feb: DuPont settled all the personal injury suits Aug: The Pentagon tested drinking water of military installations and nearby communities
2018	<ul style="list-style-type: none"> 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	<ul style="list-style-type: none"> Over 80 bills related to PFAS were introduced in the 116th Congress
2023	<ul style="list-style-type: none"> 1,938 contamination sites discovered across the U.S. (The PFAS Project Lab).
2024	<ul style="list-style-type: none"> Apr: EPA established maximum contaminant levels for PFOA (4 ppt), PFOS (4 ppt), PFHxS (10 ppt), PFNA (10 ppt), and GenX (10 ppt) in drinking water and designated PFOA and PFOS as hazardous substances under CERCLA.

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, public drinking water system of 200 counties across 33 states were discovered to be contaminated with at least one of the six PFAS chemicals. One county may become contaminated with more than one PFAS. MRL is the minimum reporting level under UCMR (3) program. Concentrations and MRL are reported 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

This table reports the summary statistics of bond and county socioeconomic variables. *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 (Tenure in years)⁻¹* is the inverse of *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. *PFAS Industry Share* is the share of industries likely affected by PFAS rulemakings in a county. *Water Code Violations* is the county-year health violations in drinking water per million population. *Ln (Num. Est.)*, *Ln (Num. Emp.)*, *Ln (Population)*, and *Ln (Personal income)* are natural logs of the number of establishments, the number of employment, population, and county-aggregated personal income in million dollars. *DuPont or 3M Plant* is a dummy variable taking the value of 1 if a DuPont, 3M, or Chemours facility is present in a county and 0 otherwise.

	N	Mean	Med.	Min.	Max.	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Bond-Level Variables</i>						
YTM(%)	100086	2.33	2.30	0.00	12.50	1.00
Coupon(%)	100919	3.51	3.25	0.04	25.22	1.14
Ln(Issue Amt.)	100285	13.46	13.24	8.52	20.80	1.48
Ln(Tenure in years)	100919	2.08	2.20	0.00	3.81	0.73
(Ln(Tenure in years)) ⁻¹	98899	0.55	0.46	0.26	1.44	0.27
Callable [= 1]	100919	0.46	0.00	0.00	1.00	0.50
Competitive Offering [= 1]	100474	0.64	1.00	0.00	1.00	0.48
Insured [= 1]	100919	0.12	0.00	0.00	1.00	0.32
<i>County × Year-Level Variables</i>						
PFAS Industry Share (%)	1610	5.49	5.50	0.00	12.75	1.41
Water Code Violations	1610	2.77	0.00	0.00	233.11	13.92
Ln(Num. Est.)	1610	8.33	8.35	4.20	12.55	1.51
Ln(Num. Emp.)	1609	11.00	11.03	6.16	15.20	1.64
DuPont or 3M Plant [= 1]	1610	0.04	0.00	0.00	1.00	0.20
Ln(Population)	1610	12.12	12.18	8.26	16.13	1.41
Ln(Personal income)	1605	9.06	9.11	4.94	13.31	1.56

Table IV: PFAS Contamination and Municipal Bond Offering Yields

This table reports the DD regressions of municipal bond offering yields around PFAS contamination discovery, as specified in equation (5). In Columns (1) and (2), the regression sample includes counties contaminated by any of the six PFAS and the bordering uncontaminated counties within the same state. In Columns (3) and (4), the regression sample includes counties contaminated by PFOA and PFOS and the bordering counties that did not detect any of the six PFAS within the same state. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. *Bond Controls* include CUSIP-level log issuance amount, log bond tenure (in years), the inverse of log bond tenure (in years), and binary variables indicating whether the bond is insured, callable, and competitively offered. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and personal income. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Contaminant =	Any PFAS		PFOA or PFOS	
	(1)	(2)	(3)	(4)
Outcome=	YTM	YTM	YTM	YTM
Treatment \times Post	0.10*** (5.31)	0.13*** (5.66)	0.11*** (5.87)	0.14*** (6.46)
Controls	Bond	Bond & County	Bond	Bond & County
FE: County, Pair \times Year, Capital	Y	Y	Y	Y
FE: Rating \times Agency	Y	Y	Y	Y
Adjusted R ²	0.84	0.84	0.84	0.84
Observations	209014	208467	210089	209591

Table V: Effect on Borrowings

This table reports the effect of contamination discovery on the changes in $\ln(\text{Bond Amt.})$, $\ln(\# \text{Bond})$, and the *Number of Bonds* at the county×year level. Columns (1) to (3) report the DD regressions for these outcomes respectively for bonds of all maturities, whereas columns (4) to (6) report the DDD regressions comparing these outcomes for long- and short-term bonds. A bond is classified long-term if its maturity is greater than 15 years. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Specification =	DD on All Maturity Borrowings			DDD on Long- vs. Short-Term Borrowings		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome =	$\ln(\text{Bond Amt.})$	$\ln(\# \text{Bond})$	# Bond	$\ln(\text{Bond Amt.})$	$\ln(\# \text{Bond})$	# Bond
Treatment × Post × Long Term				0.182*	0.112*	0.131***
				(1.75)	(1.99)	(2.62)
Treatment × Post	-0.008	-0.125	-0.016	-0.045	-0.169*	-0.028
	(-0.09)	(-1.35)	(-0.22)	(-0.53)	(-1.76)	(-0.45)
Long Term				-0.589***	-1.357***	-1.316***
				(-3.37)	(-13.33)	(-13.02)
County Controls	Y	Y	Y	Y	Y	Y
Regression	OLS	OLS	PPML	OLS	OLS	PPML
FE: County, Pair×Year	Y	Y	Y	Y	Y	Y
R ² (Adjusted/Pseudo*)	0.79	0.67	0.88*	0.74	0.75	0.85*
Observations	2024	2024	2032	6301	6301	6316

Table VI: Effect on Credit Risk

This table reports the heterogeneous effects of contamination discovery on offering yields of municipal bonds with different credit risk characteristics. Column (1) presents the differential impact on bonds not backed by taxation power relative to general obligation bonds. Column (2) presents the differential impact on the bonds issued by municipalities from the states other than the nine classified as proactive in [Gao et al. \(2019\)](#). Column (3) presents the differential impact on bonds from counties that detected all six PFAS. 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 . *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with $Treatment \times Post \times X$ captures the heterogeneous effects on different bonds characterized by X . *Bond Controls* include CUSIP-level log issuance amount, log bond tenure (in years), the inverse of log bond tenure (in years), and binary variables indicating whether the bond is insured, callable, and competitively offered. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Third Difference $X =$	—	Non-G.O.	Non-Proactive	More PFAS
	(1)	(2)	(3)	(4)
Outcome =	Rating	YTM	YTM	YTM
Treatment \times Post $\times X$		0.137*** (3.21)	0.117*** (2.89)	0.174* (1.94)
Treatment \times Post	0.043* (1.77)	0.056*** (2.91)	0.047 (1.59)	0.120*** (5.23)
Regression	PPML	OLS	OLS	OLS
Bond & County Controls	Y	Y	Y	Y
FE: County, Pair \times Year, capital	Y	Y	Y	Y
FE: Rating \times Agency/Agency*	Y*	Y	Y	Y
R ² (Adjusted/Pseudo*)	0.13*	0.84	0.84	0.84
Observations	95340	208467	208467	208467

Table VII: Mutual Funds' Allocation to Affected Municipalities

This table reports the effect of contamination discovery on the allocation decision of mutual funds in the bonds issued by municipalities from the affected and the bordering, unaffected counties. The outcome variable is the natural log of the number of bond i 's shares held by fund f in year-quarter q . The regression sample includes all funds in Column (1), retail funds in Column (2), institutional funds in Column (3), index funds in Column (4), and exchange traded funds in Column (5). *Affected Bond* equals 1 if the 6-digit CUSIP of the bond held by mutual funds matches with the 6-digit CUSIP of municipal bonds issued by the municipalities in the contaminated counties and 0 otherwise. *Post* takes the value of 1 for $qtr \geq Q3, 2016$ and 0 for the earlier periods. *Controls* include management fees, expense ratio, and the natural log of one-quarter lagged values of fund's total net assets and underlying bond's market value. Standard errors are clustered by fund. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Outcome =	Ln(# Bonds)				
	(1)	(2)	(3)	(4)	(5)
Fund Type =	All Funds	Retail Funds	Inst. Funds	Index Funds	ETFs
Affected Bond \times Post	-0.013*** (-8.21)	-0.014*** (-7.98)	-0.012*** (-3.43)	-0.004 (-0.36)	0.007 (0.44)
Controls	Y	Y	Y	Y	Y
FE: Fund, CUSIP8, Year-Quarter	Y	Y	Y	Y	Y
Adjusted R ²	0.98	0.98	0.97	0.96	0.95
Observations	1966986	1323527	640036	72340	57129

Table VIII: Treatment Effect Heterogeneity with Socio-Economic Characteristics

This table reports the heterogeneous effects of contamination discovery on offering yields of bonds issued by municipalities from counties with different socio-economic characteristics. Column (1) presents the differential impact on bonds from counties with higher homeownership rate, and column (2) and (3) with the two measures of social cohesion, higher support ratio and clustering, capturing social capital [Chetty et al. \(2022a\)](#). 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 . *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq$ August 9, 2016 and 0 for the earlier periods. The coefficient associated with $Treatment \times Post \times X$ captures the heterogeneous effects on different bonds characterized by X . *Bond Controls* include CUSIP-level log issuance amount, log bond tenure (in years), the inverse of log bond tenure (in years), and binary variables indicating whether the bond is insured, callable, and competitively offered. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Third Difference $X =$	High Homeownership	High Support Ratio	High Clustering
	(1)	(2)	(3)
Outcome =	YTM	YTM	YTM
$Treatment \times Post \times X$	-0.19* (-1.68)	-0.15*** (-2.89)	-0.17*** (-3.40)
$Treatment \times Post$	0.27** (2.43)	0.15*** (5.76)	0.16*** (6.03)
Bond & County Controls	Y	Y	Y
FE: County, Pair \times Year	Y	Y	Y
FE: Rating \times Agency, capital	Y	Y	Y
Adjusted R^2	0.84	0.84	0.84
Observations	135625	206414	206414

Table IX: Effect on Municipal Operations

This table reports the effect of contamination discovery on the changes in county revenue and expenditure at the county×year level. Columns (1) to (3) report the regressions of revenue, tax, and property tax, all in natural logs. Columns (4) and (5) report the regressions of general and general current expenditure, also in natural logs. General expenditure represents expenditures to individuals or agencies outside the government. General current expenditure refers to that part of general expenditure that is used for current operations. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Revenue Sources			Expenditure	
	(1)	(2)	(3)	(4)	(5)
Outcome (in Ln) =	Revenues	Taxes	Prop. Taxes	General	General Current
Treatment × Post	-0.042** (-2.56)	-0.053*** (-4.28)	-0.043*** (-3.93)	-0.031*** (-2.67)	-0.033*** (-2.97)
County Controls	Y	Y	Y	Y	Y
FE: County, Pair × Year	Y	Y	Y	Y	Y
Adjusted R ²	0.98	0.98	0.99	0.97	0.98
Observations	6606	6526	6520	6580	6580

Table X: Effect on Public Employment

This table reports the effect of contamination discovery on county public employment. The outcome variable is the natural log of full-time equivalent public sector employment in Column (1), the ratio of public to all employment in Column (2), and public employment per 1,000 population in Column (3). Columns (4) to (6) report the DDD regressions comparing these outcomes respectively for counties with high and low burden of interest payments. A county is classified as having high-interest burden if the ratio of total interest payments (aggregated across all municipalities and county governments) to total revenue (also similarly aggregated) was higher than the sample median in the pre-event year 2015. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Specification =	DD: All Counties			DDD: High vs. Low Interest Burden		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome =	Ln(Pub. Emp.)	$\frac{\text{Pub. Emp.}}{\text{All Emp.}}$	$\frac{\text{Pub. Emp.} \times 1000}{\text{Population}}$	Ln(Pub. Emp.)	$\frac{\text{Pub. Emp.}}{\text{All Emp.}}$	$\frac{\text{Pub. Emp.} \times 1000}{\text{Population}}$
Treatment \times Post \times Int. Burden				-0.119*	-0.011*	-1.163
				(-1.93)	(-1.89)	(-1.47)
Treatment \times Post	-0.119***	-0.006***	-1.756***	-0.040	0.001	-0.859
	(-4.26)	(-3.43)	(-5.08)	(-0.86)	(0.23)	(-1.49)
County Controls	Y	Y	Y	Y	Y	Y
FE: County, Pair \times Year	Y	Y	Y	Y	Y	Y
Adjusted R ²	0.95	0.73	0.85	0.95	0.72	0.84
Observations	5204	5272	5272	5092	5160	5160

Table XI: Effect on Out-migration

This table reports the effect of contamination discovery on migration to other counties within the same state. Dependent variable in Column (1) is the number of out-migrants of a county in natural logarithm, in Column (2) is net out-migration from a county expressed as percentages of residents, in Column (3) is the ratio of out-migrants to in-migrants, in Column (4) is county-aggregated adjusted gross income (AGI) of in-migrants scaled by that of residents, and in Column (5) is county-aggregated AGI of out-migrants scaled by that of residents. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1) Ln(Out-mig.)	(2) $\frac{(\text{Out} - \text{In}) \text{ mig.}}{\text{Res.}} \%$	(3) $\frac{\text{Out-mig.}}{\text{In-mig.}} \%$	(4) $\frac{\text{Income}[\text{In-mig.}]}{\text{Income}[\text{Res.}]} \%$	(5) $\frac{\text{Income}[\text{Out-mig.}]}{\text{Income}[\text{Res.}]} \%$
Treatment \times Post	0.024*** (3.88)	0.099** (2.51)	2.363** (2.50)	-0.154** (-2.41)	0.024 (0.37)
Ln(In-migration)	0.018 (0.49)				
County Controls	Y	Y	Y	Y	Y
FE: County, Pair \times Year	Y	Y	Y	Y	Y
Adjusted R ²	0.997	0.616	0.690	0.860	0.566
Observations	6946	6946	6946	6960	6960

Table XII: Effect on Wage and Firm Dynamics

This table reports the effect of contamination discovery on firms and jobs in tradable relative to non-tradable sectors. Column (1) reports the DDD regression of average payroll (in natural log). Columns (2) and (3) report the DDD regression of number of firm and establishment deaths using PPML regression. Column (4) and (5) report the DDD regression of number of job creation and destruction using PPML regression. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	Ln(Avg. Payroll)	# Firm Death	# Estab. Death	# Job Creation	# Job Destruction
Treatment \times Post \times Tradable	0.050** (1.99)	0.040* (1.66)	0.042* (1.72)	-0.073* (-1.93)	0.039 (0.78)
Treatment \times Post	0.006 (0.49)	-0.023*** (-2.90)	-0.025*** (-3.08)	0.002 (0.13)	-0.035** (-2.14)
Post \times Tradable	-0.007 (-0.37)	0.052*** (3.02)	0.047*** (2.67)	-0.015 (-0.70)	-0.123*** (-4.27)
Treatment \times Tradable	0.001 (0.02)	0.168 (1.25)	0.163 (1.22)	0.070 (0.74)	0.056 (0.67)
Tradable	0.695*** (29.47)	-1.650*** (-26.45)	-1.661*** (-26.81)	-0.827*** (-12.90)	-0.718*** (-14.15)
County Controls	Y	Y	Y	Y	Y
Regression	OLS	PPML	PPML	PPML	PPML
FE: County, Pair \times Year	Y	Y	Y	Y	Y
R ² (Adjusted/Pseudo*)	0.75	0.95*	0.96*	0.97*	0.97*
Observations	12525	13492	13492	14028	14028

Table XIII: Effect on Self-Employment

This table reports the effect of contamination discovery on self-employment. In Column (1) the outcome variable is the natural log of the number of nonemployer business in a county, in Column (2) it is the natural log of the number of returns with self-employment tax, and in Column (3) it is the ratio of the number of returns with self-employment tax to the number of total returns in a county expressed in percentage. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, and the natural log of the number of establishments, the number of employment, population, and aggregate personal income in a county. Control variables are defined in Table III. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Ln(# Nonemployer Business)	Ln(# Self-Emp. Ret.)	$\frac{\# \text{ Self-Emp. Ret.}}{\# \text{ All Ret.}}\%$
Treatment \times Post	0.010*** (3.83)	0.010*** (4.22)	0.130*** (3.79)
County Controls	Y	Y	Y
FE: County, Pair \times Year	Y	Y	Y
Adjusted R ²	1.00	1.00	0.99
Observations	6960	6972	6972

Table XIV: Health-Related Outcomes

Panel A reports the effect of contamination discovery on health insurance coverage, and panel B reports long-term difference in health outcomes. The outcome variable is the fraction of county population that has any health insurance in column (1) and that has private health insurance in column (2). In column (1), the outcome variable is the mortality rate per 100,000 population due to kidney cancer in a county; in column (2), it is the fraction of total singleton new births in a county where mother is reported to have preeclampsia; in column (3), it is the average number of congenital anomalies in a county per singleton birth with any congenital anomaly. *Treatment* equals 1 if the drinking water supply of a county was contaminated with PFAS and 0 otherwise. *Post* takes the value of 1 for $t \geq 2016$ and 0 for the earlier periods. *County Controls* in panel A and column (1) of panel B include the annual number of drinking water health violations, the share of establishments in PFAS-related industries, the natural log of the number of establishments and the number of employment, an indicator variable for the presence of any DuPont, 3M, or Chemours facility, the natural log of population, and aggregate personal income in a county. *County Controls* in columns (2) and (3) of panel B include only the last three variables. Standard errors are clustered by county. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

A: Effect on Health Insurance Coverage (DD Estimation)

	(1)	(2)
	Any Hlth. Ins. (%)	Pvt. Hlth. Ins. (%)
Treatment \times Post	0.387** (2.00)	0.362** (2.13)
County Controls	Y	Y
FE: County, Pair \times Year	Y	Y
Adjusted R ²	0.923	0.983
Observations	1488	1488

B: First Difference in Health Outcomes over Long-Term

	Cancer Mortality over 1999–2016	Pregnancy Outcomes over 1990–2002	
	(1)	(2)	(3)
Condition =	Kidney (/100K)	Eclampsia (%)	# Congenital Anomalies
Treatment	0.322*** (2.62)	0.051* (1.73)	0.014** (2.52)
County Controls	Y	Y	Y
FE: County Pair, Year	Y	Y	Y
Adjusted R ²	0.73	0.54	0.08
Observations	3403	6049	5917

Internet Appendix for “Municipal and Economic Consequences of PFAS Contamination Discovery”

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Table IA.I: Robustness for Table VII: Using PPML Regression

This table reports the effect of contamination discovery on the allocation decision of mutual funds in the bonds issued by municipalities from the affected and the bordering, unaffected counties. The outcome variable is the number of bond i 's shares held by fund f in year-quarter q . The regression sample includes all funds in Column (1), retail funds in Column (2), institutional funds in Column (3), index funds in Column (4), and exchange traded funds in Column (5). $Affected\ Bond_i$ equals 1 if the 6-digit CUSIP of the bond held by mutual funds matches with the 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 the 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 in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Outcome =	# Bonds (Using PPML Regression)				
	(1)	(2)	(3)	(4)	(5)
Fund Type =	All Funds	Retail Funds	Inst. Funds	Index Funds	ETFs
Affected Bond \times Post	-0.022*** (-12.35)	-0.022*** (-11.10)	-0.022*** (-5.73)	-0.003 (-0.30)	0.009 (0.57)
Controls	Y	Y	Y	Y	Y
FE: Fund, CUSIP8, Year-Quarter	Y	Y	Y	Y	Y
Pseudo R ²	0.98	0.98	0.98	0.97	0.96
Observations	1966986	1323527	640036	72340	57129