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Unregulated contaminants in drinking water: Evidence from PFAS and housing prices

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ABSTRACT

Our understanding of individuals' response to information about unregulated contaminants is limited. We leverage the highly publicized social discovery of unregulated PFAS (per- and polyfluoroalkyl substances) contamination in public drinking water to study the impact of information about unregulated contaminants on housing prices. Using residential property transaction data, we employ a difference-in-differences research design and show that high profile media coverage about PFAS contamination significantly decreased property values of affected homes. We also find suggestive evidence of residential sorting that may have worsened environmental inequality.

While the US Environmental Protection Agency (USEPA) sets enforceable standards for a variety of pollutants through regulations such as the Clean Air Act and the Safe Drinking Water Act, many potentially harmful contaminants remain unregulated and unmonitored (Levin et al., 2023). Without systematic monitoring and public notification requirements, the public has little opportunity to avoid exposure, especially when contaminants are undetectable by smell, sight or taste. While existing research has documented public response to information about a variety of regulated contaminants, we know much less about how individuals might respond to an information shock about the presence of harmful unregulated contaminants.

In this paper, we investigate the impact of an information shock about the presence of unregulated chemical contaminants in drinking water on housing prices and neighborhood sorting. We take advantage of the sharp timing of social discovery of contamination to compare home prices in contaminated water systems relative to uncontaminated water systems in a difference-in-differences research design using property-level home sales data. We also leverage information on newspaper articles covering the contamination to explore the role of media coverage and public scrutiny, and we explore impacts on residential sorting and neighborhood change using data from the Census and the Home Mortgage Disclosure Act (HMDA).

Our study focuses on the social discovery of per- and polyfluoroalkyl substances (PFAS) contamination in drinking water systems in New Jersey. PFAS are a widely used class of unregulated chemicals that are extremely resistant to degradation, are difficult to

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remove from the environment, and are undetectable in drinking water by sight, taste, or smell (Cousins et al., 2020). Adverse health effects associated with PFAS exposure include cancer, immune system hypersensitivity and suppression, endocrine disruption, and adverse reproductive outcomes (ATSDR, 2020; Averina et al., 2019; Barry et al., 2013; Fenton et al., 2021; Shane et al., 2020; Waterfield et al., 2020).

In July 2013, a nonprofit organization obtained results from tests conducted in 2009 by the New Jersey Department of Environmental Protection (NJDEP) showing significant levels of PFAS in several drinking water systems throughout the state. Contamination was of particular concern in Paulsboro, an industrial Philadelphia suburb in southwestern New Jersey. The Paulsboro Water Department had especially high levels of PFNA in one of the drinking water wells and was unable to take the well offline immediately due to naturally occurring radium in its other offline wells (Post et al., 2013).[2] Shortly after the nonprofit publicly released this information, Paulsboro received extensive attention from both the media and regulators. Not only did the NJDEP issue a public health advisory in Paulsboro (Comegno, 2014), but newspaper articles barraged residents with information about the presence of PFAS in their drinking water, and also pointed out that the contamination was initially discovered four years prior to public notification. This delayed notification may have had an impact on the public's distrust of the water system and local regulators and/or the public's perception of future contamination risk if individuals believe revealed and unobserved risks are correlated (Hausman and Stolper, 2021) .

Across multiple counterfactual groups, we find that housing prices decreased by about 31 to 42 percent in Paulsboro after the release of information about PFAS contamination in local drinking water supplies. Notably, the decreases in property values observed in Paulsboro were larger than the cost of installing a whole home filter, and we observe no rebound in property values after the contaminated source well was moved offline. This persistent and large decline in property values may reflect, in part, a lasting increase in public distrust and stigma associated with living there. We do not find any evidence of changes in housing prices in other water systems with elevated PFAS levels or in other neighborhoods close to identified PFAS polluters in general or the industrial source responsible for contamination in Paulsboro specifically. These findings are consistent with high publicity and public scrutiny of Paulsboro playing a role in the effect on housing prices. Exploring the subsequent changes in neighborhood demographics in Paulsboro relative to other areas, we observe a large decline in the proportion of the population under 18, who are more at risk from exposure, a decrease in the proportion of renter occupied homes, and an increase in the proportion of vacant homes. We also see a decrease in the proportion of white applicants for new mortgages, along with an increase in the proportion of Hispanic applicants, suggesting a possible impact on environmental justice through residential sorting.

This paper contributes to a literature spanning several disciplines that has consistently documented disproportionate pollution exposure in low-income and disadvantaged communities (Agyeman et al., 2016; Mohai et al., 2009; Tessum et al., 2021). Understanding the mechanisms behind these patterns has been the focus of much work in economics (Shapiro and Walker, 2021; Banzhaf et al., 2019; Burda and Harding, 2014). For example, previous research has documented aggregate neighborhood demographic changes in response to remediation of pollution, reflective of sorting behavior (Gamper-Rabindran and Timmins, 2011; Banzhaf and Walsh, 2008; Currie, 2011). Information has also been shown to impact avoidance behaviors (Moretti and Neidell, 2011; Neidell, 2009, 2004).[3] In the context of drinking water, public notification of poor water quality allows households to avoid exposure by drinking bottled water, for example Marcus (2022), Allaire et al. (2019), Zivin et al. (2011). Information may also impact more extreme avoidance through residential sorting (Marcus, 2021; Currie, 2011). To the extent that this behavior differs across demographic groups, it may contribute to broader patterns of elevated pollution exposure among disadvantaged communities. We provide novel evidence of the impact of new information about an unregulated contaminant on the housing market and suggestive evidence of how this may have affected residential sorting.

This study also contributes to the rich literature on how housing markets respond to changes in environmental quality. Existing work finds impacts on property values from air quality (Bayer et al., 2009; Chay and Greenstone, 2005; Smith and Huang, 1995), lead remediation (Gazze, 2021; Billings and Schnepel, 2017), hazardous waste remediation (Gamper-Rabindran and Timmins, 2013; Greenstone and Gallagher, 2008), train derailments involving hazardous materials (Tang et al., 2020), toxic plant openings and closings (Currie et al., 2015), and power plant openings (Davis, 2011). While estimates from hedonic studies theoretically measure consumer willingness to pay to avoid the particular pollution exposure, they are widely contingent on whether residents are properly informed about environmental quality. Moreover, these estimates can also capture misinformation and public stigma (McCluskey and Rausser, 2003; Boyle et al., 2010). Given that we find the impact on housing prices exceeds the cost of avoidance through purchasing a water filtration system and that housing prices remain depressed even after remediation, we interpret our large housing price impacts as reflecting, at least in part, an increase in public distrust and stigma.

A relatively small literature studies the effect of information about water contamination on property values. While many sources of pollution are already visible or publicized widely, water pollution is particularly difficult to observe compared to other types of environmental pollutants. Even when water quality data are available, it is often unclear whether residents are properly informed (Marcus, 2022). When contaminants are unregulated and unmonitored, the public is even less likely to be informed. The limited research in this area has documented that leaking underground storage tanks and nearby shale gas development impact property values for homes served by private groundwater wells (Guignet et al., 2016; Muehlenbachs et al., 2015). Surface water quality, such as harmful algal blooms, can also impact nearby property values, for example through impacts on recreational

[2] Perfluorononanoic Acid, also known as heptadecafluorononanoic acid, or PFNA, is a synthetic chemical which is part of the larger class of PFAS chemicals. There are more than 12,000 PFAS in the chemical class (USEPA, 2022), and alternatives continue to be developed (Wang et al., 2017/03/07).

[3] Imperfect information may also play an important role in generating disparities in pollution exposure (Hausman and Stolper, 2021).

activities (Melstrom, 2022; Zhang et al., 2022; Keiser and Shapiro, 2018; Leggett and Bockstael, 2000). However, research on the impact of public drinking water contamination on property values is much more limited. Christensen et al. (2023) find that information about dangerous levels of lead in drinking water in Flint, Michigan lead to significant decreases in housing values that remained depressed well after the water was declared safe for human consumption. While previous work has focused on information about regulated contaminants in public drinking water, such as lead, we show that information about the presence of harmful unregulated contaminants can yield sizable impacts on home values as well.

Studying the causal effects of unregulated contaminants, such as PFAS, poses several challenges. First, the unregulated nature of these contaminants leads to a scarcity of systematic testing, contamination, and remediation data. Thus, individuals lack information on the presence of contamination as well as the potential harms to their health, which limits their ability to avoid exposure. Given full information, individuals may prefer to avoid exposure through obtaining an alternate drinking water source or changing residential locations, for example. In addition, even if the timing of contamination is known, the persistence of PFAS in the environment means that the timing of release and human exposure may not align. Given these limitations, very few studies identify causal effects associated with exposure to PFAS (Waterfield et al., 2020), and to our knowledge no previous studies analyze how individuals change their behavior in response to information about PFAS contamination in their drinking water.

These findings are especially timely as, in April 2024, the EPA announced new drinking water standards for six PFAS, including PFNA.[4] Our findings may assist regulators in assessing the value of these new public drinking water standards that will require regular sampling for PFAS and public notification of elevated PFAS levels.

1. Background

1.1. Background on PFAS

The PFAS class consists of over 12,000 chemicals (USEPA, 2022), and the compounds are used in over 200 consumer and industrial applications, such as non-stick cookware, waterproof clothing, mattresses, carpets, cosmetics, and firefighting foam (Gluge et al., 2020). Humans are primarily exposed to PFAS through ingestion, primarily the consumption of contaminated food and drinking water and the migration of PFAS from food packaging or cookware (Domingo and Nadal, 2019). While other exposure pathways are possible, there is sparse research on exposure to PFAS through dermal uptake, i.e. absorption through the skin (Ragnarsdóttir et al., 2022). PFAS contamination in drinking water can originate from a number of point sources, including airports, military sites, and landfills, as well as from the industrial production sites of these chemicals (Hu et al., 2016).

Numerous studies have documented adverse health effects associated with exposure to PFAS, including kidney and testicular cancer, immune system hypersensitivity and suppression, endocrine disruption, and adverse reproductive outcomes including decreased fertility rates and lower birth weights (ATSDR, 2020; Averina et al., 2019; Barry et al., 2013; Fenton et al., 2021; Shane et al., 2020; Waterfield et al., 2020). Among the many possible exposure pathways, exposure through contaminated drinking water is of particular concern. Even relatively low levels of PFAS in drinking water have been shown to contribute to blood serum concentrations (Post, 2021; Hu et al., 2019; Hurley et al., 2016). Estimates suggest that about 98 percent of US residents have detectable levels of PFAS in their blood (Calafat et al., 2019) and 200 million US residents receive PFAS contaminated drinking water in the US (Andrews and Naidenko, 2020).

Most evidence of health effects from exposure to PFAS has focused on exposure to PFOA and PFOS (United States Environmental Protection Agency, 2023d).[5] Research on health effects from exposure to PFNA, in particular, is relatively sparse and inconclusive. However, there is some suggestive evidence of associations between exposure to PFNA and effects on cardiovascular disease risk, birth weight effects, and immune antibody response (ATSDR, 2021).

There are several options for water systems to remediate PFAS in drinking water. A contaminated source (such as a groundwater well) can be turned off and an alternative water source may be used, the water system can blend contaminated water with cleaner water sources to dilute the contamination, or a water system can install filtration technology to remove PFAS from drinking water prior to delivery to residents. Reverse osmosis, nano filtration, ion exchange resins, and granular activated carbon have been found to be the most effective technologies for water systems to remove PFAS from drinking water (Appleman et al., 2013, 2014; Tang et al., 2006; Xiao et al., 2017). Other water treatment technologies such as ferric or alum coagulation, granular filtration, aeration, oxidation, and disinfection are mostly ineffective for removing PFAS (Appleman et al., 2014).

Absent utility scale water treatment, households may avoid PFAS exposure in drinking water through filtering their water before consumption, purchasing bottled water, or moving residential locations. Point-of-use reverse osmosis systems and under sink dual stage filters are the most effective household systems for removing PFAS (achieving 60–70 percent removal for long chain PFASs, including PFNA), but can be expensive (Herkert et al., 2020).[6] Pitcher and fridge filters are less expensive options, but are generally less effective for removing PFAS (Herkert et al., 2020; Lacey et al., 2023).

[4] The USEPA's MCLs for perfluorooctanoic acid (PFOA) and perfluorooctanesulfonic acid (PFOS) are each 4 nanograms per liter (ng/L). The MCL for PFNA is 10 ng/L (USEPA, 2024).

[5] PFOA and PFOS are the most widely studied chemicals of the broader PFAS class. These chemicals were produced in large amounts in the U.S. for decades and garnered the earliest attention from regulators and researchers (Interstate Technology Regulatory Council, 2020).

[6] The average costs of point-of-use reverse osmosis systems range from $300 to $1,800, plus average installation cost of $1,200. Filter replacements and maintenance can cost $100 to $200 per year.

1.2. Background on Paulsboro, NJ

In this study, we focus on contamination in Paulsboro, NJ. Paulsboro is a lower-middle income suburb of Philadelphia with approximately 6,000 residents. Paulsboro is an industrial town with ties to several polluting industries. It is home to a large oil refinery, which has been listed as one of the largest polluters in the state (Romalino, 2014). Paulsboro was also the site of a train derailment in 2012 which caused release of vinyl chloride into the air (Mulvihill, 2012). Additionally, Paulsboro is located near a chemical plant in West Deptford, which was identified as the second largest industrial producer of PFNA in the world (Prevedouros et al., 2006). The plant has been linked to PFNA contamination throughout southwestern New Jersey, including in surface water, groundwater and local community water system (CWS) drinking water supplies. While the plant reportedly stopped using PFNA in 2010, environmental contamination remains widespread long after its release due to the persistence of PFAS in the environment (Cousins et al., 2020).

1.3. Early PFAS regulation and testing

New Jersey was an early adopter of testing and monitoring for several PFAS in a sample of water systems across the state. PFAS testing on a national scale was first conducted in 2013 to 2015 during the EPA's third Unregulated Contaminant Monitoring Rule (UCMR3) (United States Environmental Protection Agency, 2023a). Thus, the early discovery of PFAS contamination in public drinking water supplies in New Jersey from early testing in 2009 serves as an interesting case study for better understanding public response to information about unregulated contaminants, like PFAS. Table A1 documents a timeline including key PFAS testing initiatives.

Concern about PFAS in drinking water originated in the early 2000s after contamination from a chemical plant in Parkersburg, West Virginia garnered significant media coverage and regulatory attention.[7] In 2006, USEPA launched the PFOA Stewardship Program encouraging the leading manufacturers of PFOA to eliminate the chemicals from production and emissions, citing potential health effects (United States Environmental Protection Agency, 2023b). NJDEP first conducted PFAS testing in 2006 with a study of PFOA in 23 CWSs (Post et al., 2009). PFOA was detected in 65 percent of the samples, but concentrations were below 40 ng/L. Although there were no official health standards at that time, in 2007, NJDEP issued a preliminary drinking water guidance level for PFOA of 40 ng/L (New Jersey Department of Environmental Protection, 2021). In 2009, the EPA established provisional health advisories for PFOA at 400 ng/L and for PFOS at 200 ng/L (United States Environmental Protection Agency, 2009).

Between August 2009 and February 2010, NJDEP conducted a second PFAS study, sampling at 29 CWSs throughout the state for 10 different PFAS. These 10 individual PFAS were chosen based on available analytic capabilities (Post et al., 2013). PFAS were detected in 21 of the 29 CWSs (see Figure A1). While NJDEP contacted municipalities and told them about the PFAS detection, no residents were notified and the results were not publicly released.[8]

1.4. Timeline of public discovery of PFAS contamination in New Jersey

Between July 16 and 18th, 2013, a nonprofit organization received the PFAS sampling results from the 2009 NJDEP study through an Open Public Records Act request. Upon receiving the information, the non-profit contacted the NJDEP, made the information publicly available on their website, and contacted news media. Carluccio (2013a,b).[9] While PFAS were detected in other NJ water systems included in the 2009 NJDEP study, there were a few reasons why Paulsboro experienced relatively more scrutiny by the media and regulators.

First, the level of PFAS detected in both initial and follow-up testing in Paulsboro was very high. The NJDEP sampling results revealed that the Paulsboro Water Department had a drinking water source well with PFNA of 96 ng/L (Post et al., 2013). While PFNA is not necessarily more harmful than other individual PFAS, such as PFOA or PFOS, the level of PFNA detected in Paulsboro was the second highest level of any other individual PFAS detected during the 2009 testing.[10] At the time of testing, regulators were mainly focused on individual contaminant levels and were not necessarily concerned about the sum of several contaminants.[11]

Follow-up testing in September 2013 found even higher PFNA levels of 150 ng/L in the water delivered to residents, which was reported to be the highest level of PFNA that had ever been recorded in drinking water worldwide (Carluccio, 2013b). While there was no threshold specific to PFNA, this was significantly higher than the NJDEP's threshold of concern for PFOA of 40 ng/L. While Southeast Morris County MUA also was found to have high PFNA in the 2009 NJDEP study, a follow-up sample did not detect PFNA above the minimum reporting level of 5 ng/L (Post et al., 2013).

Second, Paulsboro was unable to take immediate action to address the contamination. Although elevated PFAS levels were detected in only one of Paulsboro's source wells, they were unable to take the contaminated well offline due to the presence of naturally occurring radium contamination in Paulsboro's other offline wells (Comegno, 2014). In contrast, other water systems with

[7] This was dramatized in the 2019 film *Dark Waters*.

[8] The 2006 and 2009 NJDEP studies were stand alone PFAS occurrence studies. Statewide, regular PFAS testing did not begin until 2019 after a state MCL for PFNA was adopted in 2018.

[9] Appendix B provides a copy of the press release on August 5th, 2013 from the nonprofit organization, the Delaware Riverkeeper Network.

[10] Brick Township was reported to have PFOA of 100 ng/L (Post et al., 2013).

[11] Even though Atlantic City had the highest total PFAS contamination across all 10 individual PFAS (see Figure A1), the highest individual contaminant detected in Atlantic City was 46 ng/L of PFHxS.

elevated levels of PFAS were able to mitigate the contamination quickly. For example, Brick Township concluded elevated PFOA contamination was originating from the Metedeconk River Watershed and were able to adjust the blending of water sources to reduce PFOA detected in drinking water (Procopio et al., 2017).

Both the elevated levels of PFNA and the inability of the Paulsboro water system to take immediate action sparked widespread scrutiny by the media and regulators. We document a sharp increase in public knowledge of the contamination in Paulsboro after July 2013, as measured by the number of newspaper articles referencing PFNA and Paulsboro.

About 6 months after the NJDEP testing data was released to the public, the mayor of Paulsboro published a letter to residents in January 2014 informing the public about the contamination and calling for action (Campbell, 2014).[12] In the same month, the NJDEP issued a public health advisory to Paulsboro for PFNA (Comegno, 2014). No other New Jersey CWSs were issued a public health advisory related to PFAS in drinking water at this time. The state public health advisory for Paulsboro recommended that infants be given "only bottled water or formula to ensure an abundance of precaution", since the contaminant was a newly investigated pollutant for which there was no federal standard in drinking water. Beginning in January 2014, residents were offered free bottled water for several months, until after the PFNA-contaminated well was taken offline (Laday, 2014).

The PFNA-contaminated well was taken offline in April 2014, after the installation of a radium treatment system at Paulsboro's two other drinking water source wells was completed (Laday, 2014). In October 2014, the NJDEP lifted its health advisory in Paulsboro, and announced that free bottled water would no longer be offered to residents after November 1.[13] A timeline of notable dates relevant to this information discovery and the subsequent events is available in Table A1.

2. Empirical strategy

To study how the information shock about the presence of unregulated contaminants in drinking water impacted households' behavior, we estimate a difference-in-differences specification. We compare changes in housing prices in drinking water systems with and without elevated contamination before and after the public release of information about PFAS levels in late 2013. Because Paulsboro received the most public scrutiny and media attention, we focus primarily on the public response in Paulsboro. We estimate:

$$Log(Price_{pcst}) = \beta_1 Post_t \times Pauslboro_s + \boldsymbol{\gamma}_s + \boldsymbol{\theta}_{ct} + \mathbf{X}_{pt} + \epsilon \tag{1}$$

for property p in county c in CWS s that sold in year-month t. In this specification, $Post_t$ = 1 if after August 2013 and $Paulsboro_s$ = 1 if property is located within the Paulsboro CWS service area.[14] In other specifications, we define treatment as properties in all water systems with any detection of PFAS, any detection of PFNA, or elevated PFAS over 50 ng/L. The specification includes CWS fixed effects, $\boldsymbol{\gamma}_s$, county-year-month fixed effects, $\boldsymbol{\theta}_{ct}$, and other property-level controls, $\mathbf{X}_{pt}$ including acres and square footage. The results are robust to using alternative sets of fixed effects and excluding property-level controls. Our main outcome of interest is the log of the sale price of the home. We also estimate the effect on the probability that the property is sold by creating a panel at the property-by-year level. We estimate:

$$AnySale_{pcsy} = \phi_1 Post_y \times Pauslboro_s + \boldsymbol{\gamma}_s + \boldsymbol{\theta}_{cy} + \mathbf{X}_{py} + \epsilon \tag{2}$$

for property p in county c in CWS s in year y. The outcome variable is equal to 1 in a year where the property was sold and 0 otherwise. Because the panel is at the year level, we include county-year fixed effects, $\boldsymbol{\theta}_{cy}$, instead of county-year-month fixed effects. There are 21 counties in New Jersey. For both regressions, standard errors are clustered at the CWS level, but we show results are robust to clustering at alternate levels and performing randomization inference. Additionally, we present specifications with alternative levels of fixed effects, including zip code, block group, and property fixed effects specifications. We also show results using an alternate set of counterfactual comparison tracts based on nearest neighbor matching to Paulsboro following Christensen et al. (2023).

We plot event study estimates of yearly changes in housing prices to assess whether housing prices were trending similarly in Paulsboro relative to control areas, prior to the social discovery of contamination. The event study specification is as follows:

$$Log(Price_{pcst}) = \sum_{\tau=2007}^{2012} \alpha_\tau 1\{y=\tau\} \times Treat_s + \sum_{\tau=2014}^{2018} \pi_\tau 1\{y=\tau\} \times Treat_s + \boldsymbol{\gamma}_s + \boldsymbol{\theta}_{ct} + \mathbf{X}_{pt} + \epsilon \tag{3}$$

where α_τ and π_τ describe the effect on housing prices in areas served by Paulsboro CWS relative to other areas for the years, y before and after information dissemination, respectively.[15] We omit the indicator for the year 2013, normalizing to zero in that year. All other variables are defined as in Eq. (1). The α_τ show the trend in housing prices before information dissemination, and the π_τ describe how housing prices evolved after information dissemination.

In order to interpret our estimates as the effect of the social discovery of PFAS in the drinking water on home prices, it must be the case that home prices in Paulsboro would have trended similarly to home prices elsewhere after 2013 in the absences of treatment. While this assumption is not directly testable, our event study estimates document parallel trends in periods prior to

[12] Appendix B provides a copy of the mayor's letter to residents.

[13] Appendix B provides a copy of the NJDEP letter lifting the health advisory.

[14] In the robustness section, we show that our results are nearly identical whether we define the post period as beginning in July, August, or September.

[15] The coefficient for 2007 includes 2007 and earlier years, but the results are not sensitive to this binning.

Table 1
Mean property characteristics.

	All NJ		Gloucester		Matched Top 20		Paulsboro	
	Before 2013 (1)	After 2013 (2)	Before 2013 (3)	After 2013 (4)	Before 2013 (5)	After 2013 (6)	Before 2013 (7)	After 2013 (8)
Sales Price	297,386	307,476	194,906	182,465	147,505	133,910	94,816	61,678
	(186,939)	(204,607)	(103,997)	(102,448)	(103,440)	(112,873)	(60,550)	(59,448)
Acres	0.35	0.35	0.37	0.37	0.18	0.17	0.18	0.16
	(0.93)	(0.89)	(0.55)	(0.56)	(0.34)	(0.24)	(0.25)	(0.100)
Sqft	1946.1	1896.2	1941.7	1865.8	1507.2	1487.5	1399.3	1405.7
	(851.3)	(800.4)	(741.0)	(682.1)	(611.6)	(576.6)	(447.2)	(423.8)
Stories	1.81	1.70	1.62	1.58	1.58	1.57	1.53	1.51
	(29.1)	(6.41)	(0.48)	(0.48)	(0.50)	(0.50)	(0.49)	(0.49)
Year Built	1960	1959	1973	1970	1952	1950	1939	1939
	(34)	(33)	(32)	(32)	(32)	(33)	(27)	(25)

Note: Table reports mean characteristics and standard deviations in parentheses for residential homes served by CWSs from 2000 to 2018 using ZTRAX data. Columns (1)–(6) report means for three different control groups: the rest of NJ in columns (1)–(2), the rest of Gloucester county in columns (3)–(4), and the top 20 matched census tracts in columns (5)–(6). Columns (7)–(8) report averages for homes served by the Paulsboro water system. Odd columns report values prior to 2013, while even columns report values for after 2013.

treatment and we provide sensitivity analysis of violations of the parallel trends assumption based on Rambachan and Roth (2023). Trends also remain parallel in the pre-period under a number of alternative specifications with different sets of fixed effects and counterfactual groups.

In addition, it is important that the stable unit treatment variable assumption holds. This assumption would be violated if, for example, households leaving Paulsboro in response to this information shock drive housing prices upward in neighboring towns. Comparing home prices in Paulsboro to neighboring areas would then overstate the impact on home prices in response to this information shock. While the small size of Paulsboro makes this unlikely, we test for spatial spillovers directly. We estimate:

$$Log(Price_{pcst}) = \psi_1 Post_t \times Pauslboro_s + \psi_2 Post_t \times Within\_Xkm_s + \boldsymbol{\gamma}_s + \boldsymbol{\theta}_{ct} + \mathbf{X}_{pt} + \epsilon \tag{4}$$

where $Within\_Xkm_s$ is equal to one if the water system is within one of the following distance ranges from the source of pollution: 5 km, 10 km, 20 km. Other variables are defined analogously to the main specification in Eq. (1). We do not detect any significant price impacts in nearby communities, which helps support this assumption.

3. Data

We combine data from a number of sources, including newspaper articles, property-level home sales data, census tract level demographic information, and geographic information on community water supply drinking water boundaries. We describe each data source in detail below.

3.1. Home sales data

Our main data on housing prices comes from the Zillow Transaction and Assessment Database (ZTRAX) data, which is a national database of real estate data managed by Zillow Inc. Property transaction data from 2000 to 2018 were restricted to arms-length single family real estate transactions with consistent geocoding (Zillow Group, 2021).[16] Table 1 shows summary statistics for home characteristics in Paulsboro and elsewhere before and after treatment. Figure A2 in the appendix shows the number of sales over time in the treatment and control groups. We observe 1,477 sales in the treatment group and 941 of those are in our repeat sale sub-sample. Property characteristics used as controls include acres and square footage.[17] Our baseline estimates exclude sales below $1,000 and above $1 million to avoid the influence of outliers in the data. In robustness exercises, we show the results are also robust to including outliers and including non-residential sales as well.

We supplement these data with an additional source of property transaction data for Gloucester County from the County Tax Assessor's office.[18] Tax assessor data include property transactions from 2011 to 2018. We restrict the sample to residential properties.[19] Square footage is used as a control.

[16] Non-arms length sales were identified based on sales amount code which indicates some non-market transactions, document type, and a variable denoting intra-family transfers.

[17] We top-code acres above 10 to reduce the influence of extreme outliers. Less than 1 percent of observations have a value over 10 acres and the results are nearly identical without this top-coding.

[18] ZTRAX data is similar but not identical to County Tax Assessor data, because both obtain data from County Tax Assessor offices. Zillow sources ZTRAX from a major large third-party provider and through an internal initiative they call County Direct. Some data coverage gaps arise through the third-party source due to both county recording procedures and the data collection process of the third party. Because of the gaps in coverage, Zillow instituted its County Direct program. This program prioritizes counties on a dimension of characteristics and supplements the third-party coverage by collecting data directly from county Assessor and Recorder's offices. (See https://www.zillow.com/research/ztrax/ztrax-faqs/ for more information.) In addition, differences across ZTRAX and County Tax Assessor data may exist due to any data editing, processing, or reclassification by Zillow or the third party provider. Some differences may also stem from when each dataset was constructed or updated.

[19] As we cannot observe "arms length sales" in the tax assessor data, we drop properties sold for less than $100 to match the range of sales values observed in the ZTRAX data. This restriction only becomes relevant in robustness tests that relax the restriction to sales between $1,000 and $1 million.

3.2. Demographic data

We have two sources of demographic data. First, to observe changes in demographics of mortgage applicants, we use data from the Home Mortgage Disclosure Act (HMDA) including the fraction of applicants by race and ethnicity, and the average loan amount and income of the applicant. We compare averages of the pre-period before social discovery (2007–2013) to the post period (2014–2017).

Second, to observe broader changes in demographics and housing characteristics, we use 5-year estimates from the American Community Survey (ACS). These data include the fraction of residents by race and ethnicity and the fraction of households with income classified as below the poverty line or low income (defined as income below 200 percent of the federal poverty level), the proportion of the population under 18, vacant households and renter-occupied households. We take the average of the 5-year estimates from the period before social discovery (2009 to 2013) and after social discovery (2018 to 2021). We exclude 5-year estimates from 2014 to 2017, because they contain values from both before and after social discovery.

In robustness checks, we also use the ACS data to construct a matched sample of census tracts using nearest neighbor matching to Paulsboro. We matched based on 2013 5-year ACS estimates of proportion Black, proportion Hispanic, proportion low income, proportion of the population under 18, proportion renter-occupied homes and median housing value. To make the sample comparable to Paulsboro, we exclude tracts that are not served by a CWS or where a large CWS (serving >10,000 people) serves more than 50 percent of the tract. The top 30 nearest neighbor matches to Paulsboro are listed in Table A2 and mapped in Figure A3.

3.3. Geographic data

As elevated PFAS levels were detected within the Paulsboro public water system, it is important to identify homes and individuals living within the water system boundaries. We obtain the geographic boundaries of each community water system service area from the NJDEP Bureau of GIS (NJDEP Bureau of GIS, 2022), which were collected and digitized to enable long term water supply planning and to aid in emergency management during drought. Figure A4 provides a map of all CWS service areas in the state in panel (a) and CWS service areas in Gloucester county in panel (b). Our main estimates focus only on homes within a CWS service area. Homes outside CWS service areas typically rely on private groundwater wells, which lack systematic monitoring and regulation. In robustness exercises, we also show our results are robust to including homes outside CWS service areas.

To combine our property-level home sales data with public water systems, we use the locations of each property from ZTRAX to identify property locations within the geographic boundaries of each CWS service area. For property transaction data from the Gloucester County Tax Assessor's office, we match transactions to parcel data (NJ Geographic Information Network, 2021) to identify properties within each CWS service area.

To combine our demographic data with public water systems, we use census tracts, the smallest geography available for both the ACS and HMDA. For Paulsboro, we use the census tract that overlaps with 99.5 percent of the Paulsboro CWS service area.[20] This tract is depicted in panel (c) of Figure A4. We compare with other census tracts in NJ, Gloucester County, and the top 20 counterfactual tracts based on nearest neighbor matching.

3.4. Newspaper data

We collect information on the number of newspaper articles referencing PFAS in drinking water from *Access World News*. We conducted an international article search of New Jersey water systems and references to PFAS. We searched ("Water System Name" AND "New Jersey") AND ("PFNA" or "PFOA" or "PFOS") from 2006 to 2018. We focus on water systems with elevated PFAS levels, defined as systems with the total sum of all tested PFAS over 50 ng/L (see Figure A1). We exclude two systems that changed names during our sample period and are therefore difficult to track over time. We count the articles by month and year for each water system.

To inform our analysis of descriptive changes in neighborhood demographics, we also look for articles in languages other than English. There were no articles found in our database in languages other than English using these search terms.[21]

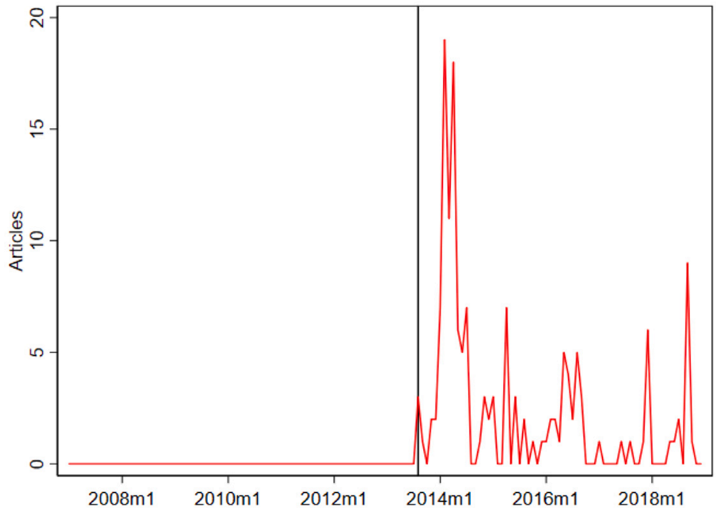
4. Results

4.1. Descriptive results

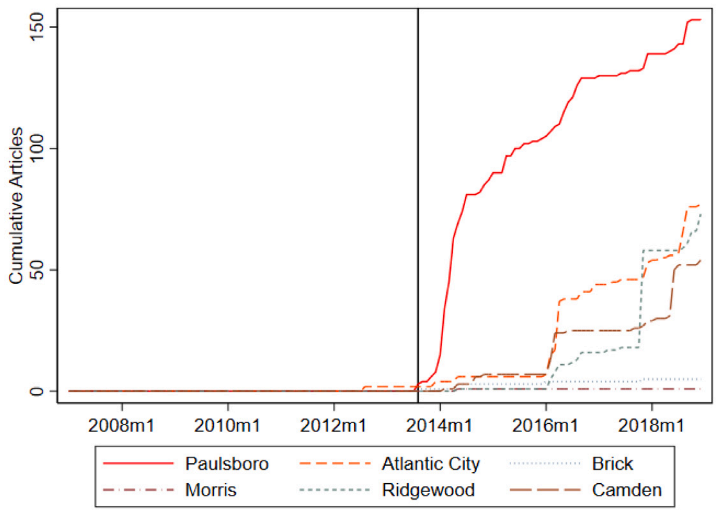
Our research design leverages the sharp timing of social discovery of PFAS contamination in Paulsboro. We start by documenting the impact and timing of newspaper coverage, as a way to measure information dissemination to the public. Using data from Access World News, Panel (a) of Fig. 1 shows the number of newspaper articles referencing PFNA and Paulsboro between 2007 and 2018. News coverage began in August 2013, denoted by a vertical line, and peaked in the beginning of 2014. Fig. 1 Panel (b) shows the

[20] There are no other CWSs that serve the Paulsboro census tract, and no other tracts that are served by the Paulsboro CWS. This is not typical, as other CWSs in NJ serve portions of multiple census tracts.

[21] Access World News includes a wide variety of global news sources from 16,379 sources, of which 567 are in Spanish. Specifically in New Jersey, there are 232 sources of which 5 are in Spanish.



(a) Paulsboro Articles per Month



(b) Cumulative Articles for Systems with PFAS

Fig. 1. News articles on PFAS.
Note: Panel (a) plots the number of newspaper articles published per month from an *Access World News* search for articles mentioning both “Paulsboro” and “New Jersey” and (“PFNA” or “PFOA” or “PFOS”). Panel (b) plots cumulative newspaper articles on PFAS for water systems with elevated detection. Searches were conducted for articles mentioning the water system name and either “PFNA” or “PFOA” or “PFOS”. The other 5 systems included in Panel (b) were selected due to elevated levels of PFAS detected in the 2009 NJDEP study, as depicted in Figure A1. Full CWS names include Paulsboro Water Department, Atlantic City MUA, Brick Township MUA, Southeast Morris County MUA, Ridgewood Water, and Camden City Department of Public Works. The vertical line denotes August 2013, when news coverage begins.

cumulative number of articles covering PFAS detection in water systems with elevated levels of PFAS in New Jersey.[22] Newspaper coverage of PFAS contamination in Paulsboro was much higher as compared to other systems.

As media coverage occurred immediately after the public release of elevated PFAS test results and coverage was concentrated in Paulsboro, our main estimates compare changes in home prices within the Paulsboro water system service area, relative to changes in home prices in other NJ water systems. Before presenting regression results, we start by showing raw differences in mean home prices. Table 1 shows mean home prices and other home characteristics for residential homes served by Paulsboro water system and other water systems, before and after 2013. Mean home prices in Paulsboro were much lower than in other CWS service areas.

[22] We report articles for systems with the total sum of all tested PFAS over 50 ng/L (see Figure A1), excluding two systems that changed names during our sample period and are therefore difficult to track over time.

Table 2
Effect on home sales in Paulsboro.

	(1)	(2)	(3)	(4)	(5)
			Panel A. Log(House Price)		
Post × Paulsboro	−0.541***	−0.561***	−0.557***	−0.569***	−0.648***
	(0.0234)	(0.0231)	(0.0226)	(0.0220)	(0.0216)
Observations	1,466,797	1,352,418	1,352,417	1,352,377	834,825
R-squared	0.436	0.537	0.596	0.643	0.803
County-year-month FE	yes	yes	yes	yes	yes
			Panel B. Pr(Any Sale)		
Post × Paulsboro	0.00192	0.00238	0.00238	0.00238	0.00171
	(0.00174)	(0.00173)	(0.00173)	(0.00173)	(0.00174)
Observations	19,036,824	17,509,113	17,509,113	17,509,113	19,036,795
R-squared	0.012	0.011	0.012	0.012	0.032
County-year FE	yes	yes	yes	yes	yes
CWS FE	yes	yes	yes	yes	
Controls		yes	yes	yes	
Zip FE			yes		
Blk group FE				yes	
Property FE					yes

Note: Table reports regression results estimating Eq. (1) using ZTRAX data from 2000–2018. The unit of observation is at the property-year-month level in Panel (a) and the property-year level in Panel (b). The outcome in Panel (a) is the log of sales price and the outcome in Panel (b) is equal to one if a property sold. The sample includes residential homes served by a CWS. $Paulsboro$ equals one if the property is located within the Paulsboro CWS service area. $Post$ equals one if the home is sold after August 2013 in Panel (a) and after 2013 in Panel (b). All columns include county-by-year-by-month fixed effects in Panel (a) and county-by-year fixed effects in Panel (b). Columns (1)-(4) include CWS fixed effects, column (2) adds controls for acres and square footage, column (3) adds zip code fixed effects, while column (4) adds block group fixed effects. Column (5) includes property level fixed effects. Standard errors are clustered at the CWS level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The average home value in Paulsboro prior to PFAS discovery was $94,816 as compared to an average of $297,386 for homes served by other water systems in NJ. When we focus on home prices in Gloucester county or in the top 20 matched census tracts, average home prices are more similar to Paulsboro. Regardless of the comparison group, after the release of information about PFAS contamination in 2013, the average home prices dropped by the largest amount in Paulsboro. After 2013, average home prices in Paulsboro dropped to $61,678. This raw comparison of means suggests that home values declined substantially in Paulsboro in response to contamination information.

4.2. Effects on property values

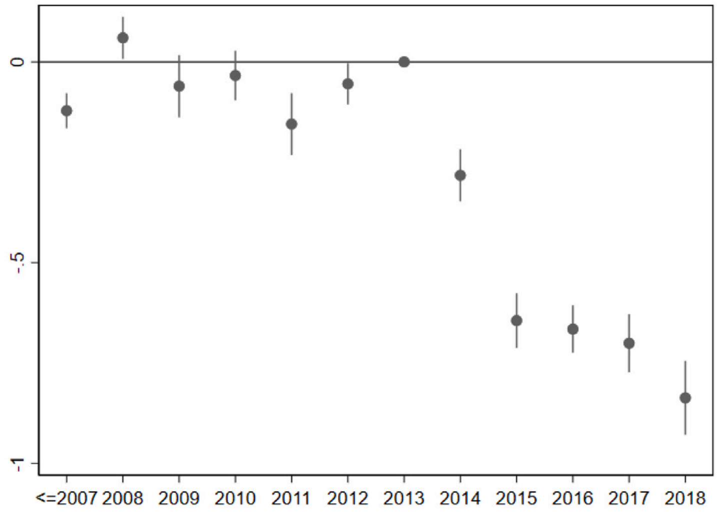
Our regression results are consistent with this raw comparison of means. We estimate our main specification of the effect on housing prices from Eq. (1) in Panel (a) of Table 2. Column (1) presents results with only county-year-month and CWS fixed effects. Column (2) includes property specific controls and represents our preferred specification from Eq. (1). Columns (3)–(5) show alternative levels of fixed effects including zip code, block group and property fixed effects, respectively. In all specifications, standard errors are clustered at the CWS level.[23] Across all specifications, we find large and statistically significant negative effects on property values in Paulsboro following discovery of PFNA contamination. In Panel (b), we estimate Eq. (2) and find little evidence of a systematic shift in the probability of homes being sold. Across specifications, we find no statistically significant changes.[24] However, it is important to note that we can only observe completed home sales and have no information on the number of homes on the market or duration of homes on the market.

Our estimates on property values range from a 42–48 percent decline within the Paulsboro CWS following the discovery of contamination.[25] Compared to the mean home value in Paulsboro prior to the discovery of PFAS contamination, $94,816, a 42 percent decline represents a decrease in home value of about $39,822. This is much larger than the cost of installing a home water filtration system to avoid exposure to contamination, which suggests that this response captures not only willingness to pay to avoid exposure, but also an increase in public distrust with respect to future contamination and the stigma associated with living in this community.

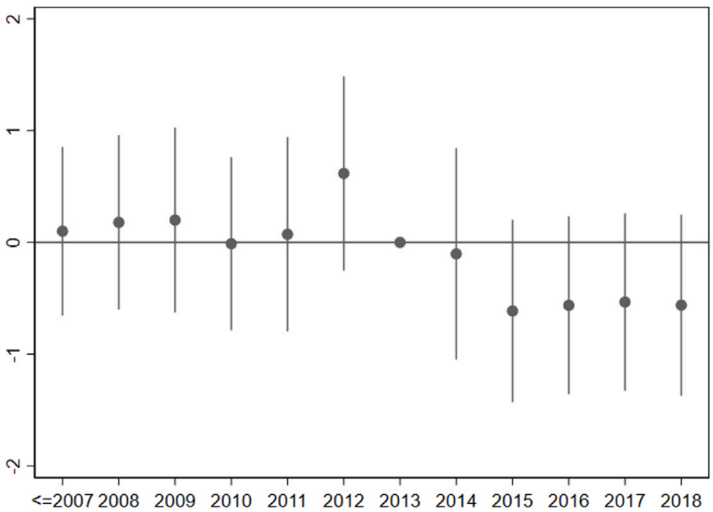
[23] Table A3 shows that the main results are robust to alternate levels of clustering. Table A4 shows our results are robust to replacing county-by-year-by-month fixed effects with county and year-by-month fixed effects.

[24] It is important to note that the type of home sold may be changing even if total sales remain constant. To the extent that home characteristics change systematically with treatment, these changes may effect our price estimates. Table A5 shows there are some changes in property characteristics after treatment, but these changes are small in magnitude and are statistically insignificant when we use the top 20 matched tracts as the counterfactual. To further address this concern, we include home characteristics as controls in all specifications and show that the results are robust after including property fixed effects, which control for all time-invariant property characteristics.

[25] Percent changes are calculated by $(e^{\beta} - 1) \times 100$.



(a) CWS fixed effects



(b) Property fixed effects

Fig. 2. Effect on log(House prices) in Paulsboro.
Note: Figure plots results from estimation of Eq. (3) using ZTRAX data from 2000–2018. The outcome is the log of sales price. The sample includes residential homes served by a CWS. The omitted reference year is 2013. All panels include year-by-month-by-county fixed effects and controls for acres and square footage. Panels (a) and (b) show results including CWS and property fixed effects, respectively. Vertical lines denote 95 percent confidence intervals. Standard errors are clustered at the CWS level in Panel (a) and at the property level in Panel (b).

Fig. 2 plots the corresponding event study style estimates from Eq. (3).[26] Panels (a) and (b) show results including CWS and property fixed effects, respectively. The omitted year is 2013, as information was released in late 2013. Across both specifications, we see little evidence of pre-trends in property values prior to social discovery of PFAS drinking water contamination in Paulsboro, which we test more formally in Section 4.2.1. This supports the assumption that property values would have trended similarly in the absence of the information shock. Yet, after information is released, we see large and persistent decreases in house prices over time, even after the contaminated well is moved offline in 2014. As property values remain depressed, even after the contamination was resolved, this further supports the idea that this information had an impact on public distrust and stigma. Figure A5 shows the event study results are very similar across alternative specifications that include zip code fixed effects and block group fixed effects. The results are also robust to including minimal fixed effects and using Gloucester county tax assessor data.

[26] Table A6 and Figure A5 replicate Table 2 and Fig. 2(a) using the Gloucester County tax assessor data rather than the ZTRAX data. Results are very similar in magnitude, although slightly smaller in the property fixed effects specification for the tax assessor data. Across all specifications results are statistically significant.

Table 3
Effects on other systems.

	(1)	(2)	(3)
Panel A. Other Systems with Detected PFAS			
Post × Paulsboro	−0.576***	−0.484***	−0.544***
	(0.0408)	(0.0621)	(0.0495)
Post × Any PFAS	0.0149		
	(0.0337)		
Post × Any PFNA		−0.0771	
		(0.0578)	
Post × Elevated PFAS			−0.0168
			(0.0438)
Panel B. Other Systems Near PFAS Facilities			
Post × Paulsboro	−0.569***	−0.561***	−0.583***
	(0.0334)	(0.0231)	(0.0302)
Post × Near Any Site	0.00860		
	(0.0265)		
Post × Near Fed Site		−0.0210	
		(0.0779)	
Post × Near PFAS Producer			0.0245
			(0.0212)
Panel C. Spatial Spillovers			
Post × Paulsboro	−0.566***	−0.575***	−0.563***
	(0.0672)	(0.0345)	(0.0232)
Post × Within 5 km	0.00720		
	(0.0703)		
Post × Within 10 km		0.0270	
		(0.0452)	
Post × Within 20 km			0.0330
			(0.0416)
Observations	1,352,418	1,352,418	1,352,418
R-squared	0.537	0.537	0.537

Note: Table reports regression results estimating Eq. (1) using ZTRAX data from 2000–2018. The outcome is the log of sales price. The sample includes residential homes served by a CWS. $Paulsboro$ equals one if the property is located within the Paulsboro CWS service area. $Post$ equals one if the home is sold after August 2013. In Panel (a), $Any\ PFAS$ and $Any\ PFNA$ are equal to one for water systems with any level of detected PFAS and PFNA in 2006–2009 testing, respectively. $Elevated\ PFAS$ is equal to one for water systems with the sum total of any PFAS category over 50 ng/L. In Panel (b), $Near\ PFAS\ Producer$ equals one if the water system is within 2km of any industrial site that manufactures or imports PFAS. $Near\ Fed\ Site$ equals one if the water system is within 2km of any federal site with known or suspected PFAS. $Near\ Any\ Site$ equals one if the water system is near either type of site. In Panel (c), $Within$ 5 km, $Within$ 10 km, and $Within$ 20 km equal one if the water system is within 5km, 10km, or 20km of the chemical plant near Paulsboro, respectively. All columns include county-by-year-by-month fixed effects, CWS fixed effects, and controls. Standard errors are clustered at the CWS level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Although Paulsboro received the vast majority of media attention and was the only water system to have a health advisory issued, it is possible that other areas with reported PFAS detections may have been impacted.[27] We test for changes in property values at other water systems with some level of detected PFAS in Panel (a) of Table 3.[28] Columns (1)–(3) define treated areas as water systems with any level of PFAS detected, any level of PFNA detected, and where the sum of all tested PFAS was over 50 ng/L, respectively. Regardless of the specification, there is no statistically significant impact on property values in these other water systems.

Similarly, if the public responded to this information by changing their perception of PFAS exposure risk from not only the chemical plant near Paulsboro, but other PFAS sources as well, we might expect to find declines in home prices near other producers and users of PFAS. We test for this in panel (b) of Table 3. We fail to find evidence of changes in property values near other suspected or known sources of PFAS.[29] Panel (b) reports changes in housing prices for homes served by other water systems that were very

[27] During the 2009 testing, water samples were collected at 29 CWSs across the state and tested for 10 different PFAS, including PFNA. Figure A1 shows the level of total PFAS (sum of the 10 PFAS tested) and level of PFNA at systems with elevated levels.

[28] Table A7 shows the robustness of these results to replacing county-by-year-by-month fixed effects from the baseline specification with county and year-by-month fixed effects.

[29] Data on suspected PFAS sources are from US EPA's PFAS Analytic Tools (United States Environmental Protection Agency, 2023c).

near, within 2 km, of any industrial site that manufactures or imports PFAS and/or any federal site with known or suspected PFAS contamination. Columns (1)–(3) show there was no statistically significant impact on property values in these other water systems after the release of information about PFAS contamination in Paulsboro.

These findings suggest that it was not simply the testing results or proximity to other suspected or known PFAS polluters that resulted in decreased home values, but that media attention played an important role. The decline in property values was unique to Paulsboro, which received the majority of negative media attention. This publicity likely increased both the salience of contamination in Paulsboro and the stigma of living in this community.

Finally, we consider whether there were spillovers to other communities nearby Paulsboro in order to test whether the stable unit treatment variable assumption holds in this setting. A priori, the direction of these spillovers is ambiguous. Nearby home prices may decrease if communities are concerned that they may also experience PFAS contamination. Alternatively, prices may increase if homeowners leaving Paulsboro move to neighboring communities, thus driving up home prices. This would bias our estimates upwards. Panel (c) of Table 3 estimates Eq. (4) and shows the change in home prices for homes served by water systems within 5 km, 10 km, and 20 km of the chemical plant near Paulsboro. Across all distances, the effects are small in magnitude and statistically insignificant. These findings suggest that the large decline in home values from this information shock was concentrated in Paulsboro, where both contamination and public scrutiny were especially high.

4.2.1. Additional robustness tests

Our main results are robust to a variety of alternative specifications and tests. First, we provide a more formal test of the parallel trends assumption. Figure A6 reports a sensitivity analysis of violations of the parallel trends assumption based on Rambachan and Roth (2023). In Panels (a) and (b), we bound the maximum post-treatment violation of parallel trends in consecutive periods by $\bar{M}$ times the maximum pre-treatment violation of parallel trends. Panels (a) and (c) focus on the first post period, 2014, while Panels (b) and (d) use the average of the post period (2014–2018). Our baseline 95 percent confidence intervals are reported in blue, and we report confidence intervals as we relax the constraint on $\bar{M}$. The decrease in house prices in Paulsboro is significant for parallel trend violations in the post period up to about 1.25 times as large as the maximum violation in the pre-treatment period for both Panels (a) and (b). Panels (c) and (d) shows the sensitivity of the results to smooth deviations from an underlying trend. We impose that the change in the slope of the trend is no more than M between consecutive periods, where M = 0 restricts violations of parallel trends to be linear. The breakdown value for M is about 0.18 in Panel (c) and 0.08 in Panel (d). This shows the result is robust to a fairly large deviation from linearity.

To the extent that one is concerned that the vinyl chloride spill from the 2012 train derailment may have contributed to the impact on housing prices we find, the parallel pre-treatment trends we observe are reassuring. If the train derailment in Paulsboro had a meaningful impact on housing prices, we should expect to see effects arising a year earlier, but our event-study figures do not show any pre-trends and are robust to the sensitivity analysis described above. Moreover, we think that any impact on local housing prices from the train derailment is likely to be temporary and relatively small in magnitude for a few reasons. First, the vinyl chloride was released into the air and did not enter the water system. NJDEP concluded that most of the contaminant dissipated quickly with exposures highest in the first 1-2 hours after the derailment in the area closest to the site (New Jersey Department of Environmental Protection, 2014). Second, even if there were a delayed impact of the train derailment on housing prices, the existing empirical research shows that the effect of train derailments involving hazardous materials is relatively small and temporary. Tang et al. (2020) find that derailments of trains involving hazardous materials depreciate housing values within a one-mile radius by 5–8 percent, which is small relative to our estimated effect on housing prices. Moreover, the authors find that housing prices of affected properties return to pre-accident levels after about 480 days. In contrast, our effects persist for at least 5 years.

Next, Table A8 presents results from a variety of robustness tests. Panel (a) uses the full sample of ZTRAX data, Panel (b) restricts the ZTRAX data to include only Gloucester county sales from 2011–2018 in order to compare to the Gloucester county tax assessor data in Panel (c). Column (1) replicates the main specification across all three different datasets. First, we explore whether the results are sensitive to including outliers in sales price. While our main results restrict to sales between \$1,000 and \$1 million, columns (2)–(4) show the results are not sensitive to this choice. Column (2) includes all sales, column (3) restricts only to sales below \$1 million, and column (4) restricts only to sales above \$1,000. Our main results remain significant across each specification. The magnitudes are remarkably similar, with the exception of columns (2) and (3) for the tax assessor data in Panel (c). These are the specifications that include property transactions where the sale price is less than \$1,000. The difference in results likely reflects our inability to directly identify arms-length transactions in the tax assessor data, unlike the ZTRAX data. Thus, many of the transactions with low sale prices likely reflect non-arms length transactions.

While our main specification restricts to residential properties served by community water systems, we show that our results are not sensitive to this sample choice. We show in column (5) that the results remain statistically significant when we include non-residential properties. The magnitude is very similar in the tax assessor data and only slightly smaller in the ZTRAX data. Next, column (6) shows the robustness to including rural properties reliant on private wells as additional controls. In this specification, we cluster at the block group level instead of CWS level since not all properties are assigned to a CWS. To ensure that our control group is not experiencing any impact of the information shock, Column (7) excludes any properties served by other CWSs that found positive PFAS levels in the 2009 NJDEP testing. However, we do not see much change in the results when these properties are excluded. This is not surprising, given we observed no change in property values for these properties in panel (a) of Table 3.

We also show in Table A9 that our results are not sensitive to alternate definitions of the post period. Our regression results define home sales as treated if they occur in September 2013 or later. As the first information on PFAS contamination in newspapers is recorded in August 2013 and the average time to close on a home purchase is typically 30–45 days, we expect that sales in August

Table 4
ACS: Changes in demographics.

	All NJ		Gloucester		Matched top 20		Paulsboro	
	Before 2013 (1)	After 2013 (2)	Before 2013 (3)	After 2013 (4)	Before 2013 (5)	After 2013 (6)	Before 2013 (7)	After 2013 (8)
Population	4,378	4,279	4,586	4,425	4,135	4,088	6,114	5,989
White, non-Hispanic	58.99	54.43	82.47	78.91	52.66	46.12	55.45	55.46
Black, non-Hispanic	14.62	13.87	8.96	9.22	27.55	29.14	33.97	29.09
Hispanic	17.15	20.32	4.48	6.55	13.54	17.3	5.82	8.98
Low Income	24.00	23.82	18.71	17.93	35.7	35.53	41.78	37.45
Below Poverty Line	10.39	10.65	7.77	7.81	15.59	16.21	23.37	14.81
Children under 18 Households	23.18	21.65	23.47	21.66	26.39	23.28	30.19	16.45
Vacant Homes	9.21	9.16	5.41	6.78	9.74	13.51	10.82	17.83
Renter-Occupied Homes	35.15	37.12	18.57	19.86	39.18	42.99	40.19	27.96

Note: Table reports summary statistics by Census Tract from ACS 5 year estimates. After 2013 consists of ACS 5 year estimates starting with 2018 to exclude 5 year estimates that include both before and after 2013. Notably, Paulsboro predominately consists of one Census Tract depicted in panel (c) of Figure A4. All NJ consists of all non-Paulsboro census tracts in NJ, Gloucester consists of all non-Paulsboro census tracts in Gloucester County, Matched Top 20 consists of 20 nearest neighbor matches of other census tracts to Paulsboro, NJ.

Table 5
HMDA: Characteristics of mortgage applications.

	All NJ		Gloucester		Matched Top 20		Paulsboro	
	Before 2013 (1)	After 2013 (2)	Before 2013 (3)	After 2013 (4)	Before 2013 (5)	After 2013 (6)	Before 2013 (7)	After 2013 (8)
White, non-Hispanic	57.39	55.13	81.36	79.72	54.02	52.00	71.83	59.81
Black, non-Hispanic	10.19	10.14	5.10	6.55	21.34	22.55	14.92	15.05
Hispanic	13.41	15.80	3.15	4.18	11.74	13.96	5.85	13.70
Loan Amount	270,494	285,678	193,208	191,201	153,414	149,368	117,025	104,882
Applicant Income	112,880	118,987	84,814	90,046	63,801	68,523	52,480	55,204
Percent Income over 70k	63.54	66.41	51.15	56.54	30.56	36.13	14.03	17.37

Note: Table reports summary statistics of mortgage applicants from Home Mortgage Disclosure Act (HMDA) data. All NJ consists of all non-Paulsboro census tracts in NJ, Gloucester consists of all non-Paulsboro census tracts in Gloucester County, Matched Top 20 consists of 20 nearest neighbor matches of other census tracts to Paulsboro, NJ.

were initiated prior to the release of information. Nevertheless, we show that our results are nearly identical whether we define the post period as beginning in July, August, or September.

Next, we use randomization inference to test the robustness of our main estimate on property values. We randomly assign placebo treatment across all community water supply systems in the data. The "randomized inference p-value" is 0.027, which is based on the proportion of placebo point estimates that are larger in magnitude than the main point estimate. Figure A7 shows the distribution of placebo point estimates is centered around zero, as expected, and the vertical line denotes our main estimate, which is in the lower tail of the distribution. This gives additional confidence that our estimated effect is statistically significant.

Finally, we also consider an alternate set of counterfactual comparison tracts based on nearest neighbor matching. As described in Section 3, we construct a counterfactual sample of census tracts matched to Paulsboro based on the proportion Black, proportion Hispanic, proportion low income, proportion of the population under 18, proportion renter-occupied homes and median housing value. We focus on the top 20 matched tracts for simplicity, but show the results are robust to using the top 30, top 20, or top 10 in Table A10. Figure A8 shows the event study figures using the top 30, top 20, or top 10 matched tracts as the counterfactual. For both the specification using CWS fixed effects in panel (a) and the specification using property fixed effects in panel (b), the results are very similar to the main specifications and show little evidence of any pre-trends. Next, Table A11 replicates the main results using the top 20 matched census tracts as the counterfactual. Across all specifications, the results for home sales price remain statistically significant. The magnitude is somewhat smaller than our main specification, but still suggests a large and significant decline in home values of about 31–33 percent. Lastly, we repeat the robustness exercises from Table A8 for the matched counterfactual specification in Table A12. The estimates remain similar across all robustness checks as well.

4.3. Effect on sorting and neighborhood characteristics

Given the large decrease in property values we document, it is important to consider how this information shock may have impacted residential sorting and broader changes in neighborhood characteristics. While we cannot observe property-level demographic characteristics, we explore descriptive changes in neighborhood demographics and housing characteristics in Paulsboro before and after information about the drinking water contamination was discovered. Table 4 compares demographic and housing characteristics before and after 2013 in Paulsboro compared to three counterfactuals, including the rest of New Jersey, the rest of Gloucester County, and the top 20 matched census tracts from the nearest neighbor matching described in Section 3.

Before 2013, compared to the rest of New Jersey in column (1), Paulsboro had a smaller fraction of white residents and higher fractions of Black residents, households below the poverty line or classified as low-income, and a slightly higher fraction of renter-occupied homes. These patterns are even more pronounced when comparing Paulsboro to other census tracts in Gloucester County in column (3). These patterns are consistent with the broader environmental justice literature that has documented higher exposure to pollution among disadvantaged communities in the cross-section. As expected, the top 20 matched census tracts from the nearest neighbor matching shown in column (5) are much more similar to Paulsboro before 2013.

After 2013, one notable change in Paulsboro is a large decrease in the fraction of children under 18, which declined by almost 14 percentage points from about 30 percent to 16 percent. For non-Paulsboro areas, there was also a decline in the population-share of children, but it was much smaller, representing just a 2–3 percentage point change. Because children are still developing, they may be more sensitive to the harmful effects of PFAS. The large decline in the share of children under 18 in Paulsboro relative to other areas after treatment may reflect higher avoidance among families with children, due to parental concern over the health risks of PFAS exposure for children.

In addition, both the fraction of households below the poverty line and the fraction of renter-occupied households decreased in Paulsboro after 2013. We do not observe similar declines for non-Paulsboro neighborhoods. This may indicate that many renter-occupied households with children, which are more likely to be low-income, were more likely to leave Paulsboro after learning about the drinking water contamination. Consistent with the reduced desirability of this neighborhood, we also see a relative increase in the share of vacant homes in Paulsboro after 2013. The share of vacant homes in Paulsboro increased by about 7 percentage points. Compared to renters, homeowners typically have higher moving costs.

To explore the changes in homeowner demographics further, Table 5 compares the demographics of applicants for new mortgages before and after 2013 in Paulsboro compared to three counterfactuals, including the rest of New Jersey, the rest of Gloucester County, and the top 20 matched census tracts. We see a large decrease in share of white, non-Hispanic applicants for new mortgages and an increase in the share of Hispanic applicants in Paulsboro after the contamination was discovered in 2013. The decrease in the share of white, non-Hispanic applicants for non-Paulsboro areas are much smaller in magnitude. While changes in demographics are less pronounced in the ACS data, which includes renters and residents who are not moving, a decrease in white mortgage applicants is an indicator that the relative demand for homes in Paulsboro decreased for white New Jersey homebuyers, and increased among Hispanic homebuyers. However, we do not see large changes in the share of lower-income mortgage applicants in Paulsboro relative to other areas. The increase in the share of Hispanic applicants, in particular, may be explained by the salience of information about drinking water contamination if English proficiency among the Hispanic population is lower than the non-Hispanic population, and if most of the information was presented in English. Based on our newspaper article search, we did not find any articles about PFAS in Paulsboro drinking water that were published in Spanish. In addition, existing literature has documented lower perceived tap water safety and higher bottled water consumption among Hispanics in the US (Pierce and Gonzalez, 2017; Drewnowski et al., 2013; Hobson et al., 2007). To the extent that Hispanic households were already distrustful of public drinking water and already avoiding tap water consumption, this information shock may had less of an impact on their perception of neighborhood quality.

Overall, these patterns document the differential demographic sorting behaviors that accompany the large decline in housing values in Paulsboro. Persistence in the property value decline and the relative increase in vacant homes in this neighborhood may also lead to deterioration in public services and other amenities.

5. Discussion & conclusion

We find that high profile media coverage about unregulated contaminants in drinking water significantly impacted housing values in Paulsboro. We find a large statistically significant decrease in home values of about 31 to 42 percent on average after the social discovery of contamination for properties within the Paulsboro water system service area relative to properties in the top 20 matched census tracts or other properties across the state. This decline was concentrated in Paulsboro, the community which received the greatest publicity in the news, suggesting the public scrutiny through the media may have increased the salience of contamination in this community and also the perceived risk and stigma associated with living there. As this contamination was hidden from the public for four years prior to public notification, public distrust may have contributed to housing prices remaining depressed even after remediation.

This 31 to 42 percent decline in property values is large relative to the cost of installing a whole home water filtration system. Yet, this effect likely reflects, at least in part, an increase in public distrust and stigma surrounding the contamination in Paulsboro. While Paulsboro received significant media attention and scrutiny by regulators from August 2013 through April 2014, we observe the negative effects on housing values were sustained through at least 2018, long after the contaminated source well was taken offline, suggesting that the perceived risk of future environmental concerns may be an important driver of households' willingness to pay. Moreover, a history of environmental issues stemming from the presence of several large oil and gas facilities and the 2012 vinyl chloride spill may have led to increasing distrust of the local government in Paulsboro and may have set the stage for these large effects.

Our estimates of a 31 to 42 percent decrease in property values represent a change in value of about $29,393 to $39,822 relative to the pre-treatment mean in Paulsboro. Similarly large housing price effects have been estimated for other drinking water crises. Following the switch in the water supply that exposed residents to elevated levels of lead, housing values in Flint, Michigan declined by 27 to 43 percent (Christensen et al., 2023). In terms of total valuation, the PFAS contamination in Paulsboro led to a decline in housing values of about \$34 to \$46 million in total.[30]

The decline in property values in Paulsboro was accompanied by changes in neighborhood demographics in Paulsboro relative to other areas. Large declines in the proportion of the population under 18 may reflect the greater risk of harm to children from exposure to PFAS. We also document a decrease in the proportion of renter occupied households and an increase in the proportion of vacant homes, relative to other areas. Higher moving costs for homeowners and the large negative shock to their home value may have limited homeowners' ability to relocate. We also document a relative decrease in the percent of white applicants for new mortgages, along with an increase in the proportion of Hispanic applicants. These findings contribute to our understanding of the mechanisms behind the widely documented disproportionate exposure to pollution among disadvantaged communities and how high profile media coverage about pollution exposure in a community may lead to residential sorting that may exacerbate environmental inequality.

Our estimates contribute to the ongoing policy discussion surrounding the regulation of PFAS. These results are especially timely given the EPA's April 2024 announcement of new federal drinking water standards for PFAS that are lower than all existing PFAS standards. The rule will require systems to monitor, notify the public, and remediate if the standards are violated (United States Environmental Protection Agency, 2023e). Improvements to public notification and transparency of drinking water quality may mitigate the likelihood that another high profile contamination event increases public distrust and stigma, causing sustained reputational damage and property value declines, in other local communities.

CRediT authorship contribution statement

Michelle Marcus: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rosie Mueller:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.102987.

References

Agyeman, Julian, Schlosberg, David, Craven, Luke, Matthews, Caitlin, 2016. Trends and directions in environmental justice: From inequity to everyday life, community, and just sustainabilities. In: Gadgil, A., Gadgil, T.P. (Eds.), Annual Review of Environment and Resources. In: Annual Review of Environment and Resources, vol. 41, pp. 321–340.

Allaire, Maura, Mackay, Taylor, Zheng, Shuyan, Lall, Upmanu, 2019. Detecting community response to water quality violations using bottled water sales. Proc. Natl. Acad. Sci. 116 (42), 20917–20922.

Andrews, David Q., Naidenko, Olga, 2020. Population-wide exposure to per- and polyfluoroalkyl substances from drinking water in the United States. Environ. Sci. Technol. Lett. 7 (12), 931–936.

Appleman, Timothy D., Dickenson, Eric R.V., Bellona, Christopher, Higgins, Christopher P., 2013. Nanofiltration and granular activated carbon treatment of perfluoroalkyl acids. J. Hazard. Mater. 260, 740–746.

Appleman, Timothy D., Higgins, Christopher P., Quinones, Oscar, Vanderford, Brett J., Kolstad, Chad, Zeigler-Holady, Janie C., Dickenson, Eric R.V., 2014. Treatment of poly- and perfluoroalkyl substances in U.S. full-scale water treatment systems. Water Res. 51, 246–255.

ATSDR, 2020. PFAS Exposure Assessments. Agency for Toxic Substances and Disease Registry (ATSDR) / Centers for Disease Control and Prevention (CDC).

ATSDR, 2021. Toxicological Profile for Perfluoroalkyls. Agency for Toxic Substances and Disease Registry (ATSDR) / Centers for Disease Control and Prevention (CDC).

Averina, Maria, Brox, Jan, Huber, Sandra, Furberg, Anne-Sofie, Sorensen, Martin, 2019. Serum perfluoroalkyl substances (PFAS) and risk of asthma and various allergies in adolescents. The tromso study fit futures in Northern Norway. Environ. Res. 169, 114–121.

Banzhaf, Spencer, Ma, Lala, Timmins, Christopher, 2019. Environmental justice: The economics of race, place, and pollution. J. Econ. Perspect. 33 (1), 185–208.

Banzhaf, H. Spencer, Walsh, Randall P., 2008. Do people vote with their feet? An empirical test of Tiebout's mechanism. Am. Econ. Rev. 98 (3), 843–863.

Barry, Vaughn, Winquist, Andrea, Steenland, Kyle, 2013. Perfluorooctanoic acid (PFOA) exposures and incident cancers among adults living near a chemical plant. Environ. Health Perspect. 121 (11-12), 1313–1318.

Bayer, Patrick, Keohane, Nathaniel, Timmins, Christopher, 2009. Migration and hedonic valuation: The case of air quality. J. Environ. Econ. Manag. 58 (1), 1–14.

Billings, Stephen B., Schnepel, Kevin T., 2017. The value of a healthy home: Lead paint remediation and housing values. J. Public Econ. 153, 69–81.

Boyle, Kevin J., Kuminoff, Nicolai V., Zhang, Congwen, Devanney, Michael, Bell, Kathleen P., 2010. Does a property-specific environmental health risk create a "neighborhood" housing price stigma? Arsenic in private well water. Water Resour. Res. 46 (3).

Burda, Martin, Harding, Matthew, 2014. Environmental justice: Evidence from superfund cleanup durations. J. Econ. Behav. Organ. 107, 380–401.

[30] There are 1,448 parcels within the Paulsboro water system boundaries and we estimate that about 80 percent of these are single family residential homes based on the percent of occupied housing units that are detached one-unit homes in 2018 ACS data.

Calafat, Antonia M., Kato, Kayoko, Hubbard, Kendra, Jia, Tao, Botelho, Julianne Cook, Wong, Lee-Yang, 2019. Legacy and alternative per- and polyfluoroalkyl substances in the U.S. general population: Paired serum-urine data from the 2013–2014 national health and nutrition examination survey. Environ. Int. 131, 105048.

Campbell, Brad, 2014. Paulsboro puts polluter on notice. Del. Riverkeeper Netw..

Carluccio, Tracy, 2013a. Delaware riverkeeper network petitions federal agency to address contaminated drinking water in new jersey. Del. Riverkeeper Netw..

Carluccio, Tracy, 2013b. Drinking water contamination in paulsboro requires urgent attention. Del. Riverkeeper Netw..

Chay, Kenneth, Greenstone, Michael, 2005. Does air quality matter? Evidence from the housing market. J. Polit. Econ. 113 (2), 376–424.

Christensen, Peter, Keiser, David A., Lade, Gabriel E., 2023. Economic effects of environmental crises: Evidence from flint, michigan. Am. Econ. J.: Econ. Policy 15 (1), 196–232.

Comegno, Carol, 2014. Contaminant at west deptford plant draws state advisory. Courier-Post.

Cousins, Ian T., Dewitt, Jamie C., Glüge, Juliane, Goldenman, Gretta, Herzke, Dorte, Lohmann, Rainer, Ng, Carla A., Scheringer, Martin, Wang, Zhanyun, 2020. The high persistence of PFAS is sufficient for their management as a chemical class. Environ. Sci.: Processes Impacts 22 (12), 2307–2312.

Currie, Janet, 2011. Inequality at birth: Some causes and consequences. Amer. Econ. Rev. 101 (3), 1–22.

Currie, Janet, Davis, Lucas, Greenstone, Michael, Walker, Reed, 2015. Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. Amer. Econ. Rev. 105 (2), 678–709.

Davis, Lucas W., 2011. The effect of power plants on local housing values and rents. Rev. Econ. Stat. 93 (4), 1391–1402.

Domingo, Jose L., Nadal, Marti, 2019. Human exposure to per-and polyfluoroalkyl substances (PFAS) through drinking water: A review of the recent scientific literature. Environ. Res. 177.

Drewnowski, Adam, Rehm, Colin D., Constant, Florence, 2013. Water and beverage consumption among children age 4-13y in the united states: analyses of 2005–2010 NHANES data. Nutrition J. 12, 1–9.

Fenton, Suzanne E., Ducatman, Alan, Boobis, Alan, DeWitt, Jamie C., Lau, Christopher, Ng, Carla, Smith, James S., Roberts, Stephen M., 2021. Per- and polyfluoroalkyl substance toxicity and human health review: Current state of knowledge and strategies for informing future research. Environ. Toxicol. Chem. 40 (3, SI), 606–630.

Gamper-Rabindran, Shanti, Timmins, Christopher, 2011. Hazardous waste cleanup, neighborhood gentrification, and environmental justice: Evidence from restricted access census block data. Amer. Econ. Rev. 101 (3), 620–624.

Gamper-Rabindran, Shanti, Timmins, Christopher, 2013. Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. J. Environ. Econ. Manag. 65 (3), 345–360.

Gazze, Ludovica, 2021. The price and allocation effects of targeted mandates: Evidence from lead hazards. J. Urban Econ. 123, 103345.

Gluge, Juliane, Scheringer, Martin, Cousins, Ian T., DeWitt, Jamie C., Goldenman, Gretta, Herzke, Dorte, Lohmann, Rainer, Ng, Carla A., Trier, Xenia, Wang, Zhanyun, 2020. An overview of the uses of per- and polyfluoroalkyl substances (PFAS). Environ. Sci.: Processes Impacts 22, 2345–2373.

Greenstone, Michael, Gallagher, Justin, 2008. Does hazardous waste matter? Evidence from the housing market and the superfund program*. Q. J. Econ. 123 (3), 951–1003.

Guignet, Dennis, Walsh, Patrick J., Northcutt, Rachel, 2016. Impacts of ground water contamination on property values: Agricultural run-off and private wells. Agric. Resour. Econ. Rev. 45 (2), 293–318.

Hausman, Catherine, Stolper, Samuel, 2021. Inequality, information failures, and air pollution. J. Environ. Econ. Manag. 110, 102552.

Herkert, Nicholas J, Merrill, John, Peters, Cara, Bollinger, David, Zhang, Sharon, Hoffman, Kate, Ferguson, P Lee, Knappe, Detlef RU, Stapleton, Heather M, 2020. Assessing the effectiveness of point-of-use residential drinking water filters for perfluoroalkyl substances (PFASs). Environ. Sci. Technol. Lett. 7 (3), 178–184.

Hobson, Wendy L, Knochel, Miguel L, Byington, Carrie L, Young, Paul C, Hoff, Charles J, Buchi, Karen F, 2007. Bottled, filtered, and tap water use in latino and non-latino children. Arch. Pediatr. Adolesc. Med. 161 (5), 457–461.

Hu, Xindi C., Andrews, David Q., Lindstrom, Andrew B., Bruton, Thomas A., Schaider, Laurel A., Grandjean, Philippe, Lohmann, Rainer, Carignan, Courtney C., Blum, Arlene, Balan, Simona A., Higgins, Christopher P., Sunderland, Elsie M., 2016. Detection of poly- and perfluoroalkyl substances (PFASs) in US drinking water linked to industrial sites, military Fire Training Areas, and wastewater treatment plants. Environ. Sci. Technol. Lett. 3 (10), 344–350.

Hu, Xindi C., Tokranov, Andrea K., Liddie, Jahred, Zhang, Xianming, Grandjean, Philippe, Hart, Jaime E., Laden, Francine, Sun, Qi, Yeung, Leo W.Y., Sunderland, Elsie M., 2019. Tap water contributions to plasma concentrations of poly- and perfluoroalkyl substances (PFAS) in a nationwide prospective cohort of U.S. women. Environ. Health Perspect. 127 (6), 067006.

Hurley, Susan, Houtz, Erika, Goldberg, Debbie, Wang, Miaomiao, Park, June-Soo, Nelson, David O., Reynolds, Peggy, Bernstein, Leslie, Anton-Culver, Hoda, Horn-Ross, Pamela, Petreas, Myrto, 2016. Preliminary associations between the detection of perfluoroalkyl acids (PFAAs) in drinking water and serum concentrations in a sample of california women. In: Environmental Science & Technology Letters. Environ. Sci. Technol. Lett. 3 (7), 264–269.

Interstate Technology Regulatory Council, 2020. History and use of per- and polyfluoroalkyl substances (PFAS) found in the environment. https://pfas-1.itrcweb.org/wp-content/uploads/2020/10/history_and_use_508_2020Aug_Final.pdf. (Accessed 10 January 2024).

Keiser, David A., Shapiro, Joseph S., 2018. Consequences of the clean water act and the demand for water quality*. Q. J. Econ. 134 (1), 349–396.

Lacey, Anthony, Evans, Sydney, Stoiber, Tasha, 2023. Getting 'forever chemicals' out of drinking water: Ewg's guide to PFAS water filters. https://www.ewg.org/research/getting-forever-chemicals-out-drinking-water-ewgs-guide-pfas-water-filters. (Accessed 10 August 2023).

Laday, Jason, 2014. DEP lifts paulsboro water advisory, solvay to cease free bottled water. South Jersey Times.

Leggett, Christopher G., Bockstael, Nancy E., 2000. Evidence of the effects of water quality on residential land prices. J. Environ. Econ. Manag. 39 (2), 121–144.

Levin, Ronnie, Villanueva, Cristina M., Beene, Daniel, Cradock, Angie L., Donat-Vargas, Carolina, Lewis, Johnnye, Martinez-Morata, Irene, Minovi, Darya, Nigra, Anne E., Olson, Erik D., et al., 2023. US drinking water quality: exposure risk profiles for seven legacy and emerging contaminants. J. Exposure Sci. Environ. Epidemiol..

Marcus, Michelle, 2021. Going beneath the surface: Petroleum pollution, regulation, and health. Am. Econ. J.: Appl. Econ. 13 (1), 72–104.

Marcus, Michelle, 2022. Testing the water: Drinking water quality, public notification, and child outcomes. Rev. Econ. Stat. 104 (6), 1289–1303.

McCluskey, Jill J., Rausser, Gordon C., 2003. Stigmatized asset value: Is it temporary or long-term? Rev. Econ. Stat. 85 (2), 276–285.

Melstrom, Richard T., 2022. Residential demand for sediment remediation to restore water quality: Evidence from milwaukee. J. Environ. Econ. Manag. 116, 102731.

Mohai, Paul, Pellow, David, Roberts, J. Timmons, 2009. Environmental justice. Annual Review of Environment and Resources, Annu. Rev. Environ. Resour. Annual Review of Environment and Resources, 34.405–430,

Moretti, Enrico, Neidell, Matthew, 2011. Pollution, health, and avoidance behavior. J. Hum. Resour. 46 (1), 154–175.

Muehlenbachs, Lucija, Spiller, Elisheba, Timmins, Christopher, 2015. The housing market impacts of shale gas development. Amer. Econ. Rev. 105 (12), 3633–3659.

Mulvihill, Geoff, 2012. Delicate cleanup ahead after NJ train derailment. Spokesman Rev..

Neidell, Matthew, 2004. Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. J. Health Econ. 23 (6), 1209–1236.

Neidell, Matthew, 2009. Information, avoidance behavior, and health. J. Hum. Resour. 44 (2), 450–478.

New Jersey Department of Environmental Protection, 2014. Paulsboro train derailment and vinyl chloride release, november 30, 2012 health survey findings and air quality impacts. https://www.nj.gov/health/ceohs/documents/eohap/haz_sites/gloucester/train_derail/factsheet.pdf. (Accessed 14 January 2024).

New Jersey Department of Environmental Protection, 2021. Contaminants of emerging concern. https://www.nj.gov/dep/srp/emerging-contaminants/. (Accessed 9 January 2023).

NJ Geographic Information Network, 2021. Parcels. https://nj.gov/njgin/edata/parcels/#!/. (Accessed 15 November 2022).

NJDEP Bureau of GIS, 2022. Purveyor service areas of new jersey. https://njogis-newjersey.opendata.arcgis.com/datasets/00e7ff046ddb4302abe7b49b2ddee07e/. (Accessed 15 November 2022).

Pierce, Gregory, Gonzalez, Silvia, 2017. Mistrust at the tap? Factors contributing to public drinking water (mis) perception across US households. Water Policy 19 (1), 1–12.

Post, Gloria B., 2021. Recent US state and federal drinking water guidelines for per- and polyfluoroalkyl substances. Environ. Toxicol. Chem. 40 (3), 550–563.

Post, Gloria B., Louis, Judith B., Cooper, Keith R., Boros-Russo, Betty Jane, Lippincott, R. Lee, 2009. Occurrence and potential significance of perfluorooctanoic acid (PFOA) detected in new jersey public drinking water systems. Environ. Sci. Technol. 43 (12), 4547–4554.

Post, Gloria B., Louis, Judith B., Lippincott, R. Lee, Procopio, Nicholas A., 2013. Occurrence of perfluorinated compounds in raw water from New Jersey public drinking water systems. Environ. Sci. Technol. 47 (23), 13266–13275.

Prevedouros, Konstantinos, Cousins, Ian T., Buck, Robert C., Korzeniowski, Stephen H., 2006. Sources, fate and transport of perfluorocarboxylates. Environ. Sci. Technol. 40 (1), 32–44.

Procopio, Nicholas A., Karl, Robert, Goodrow, Sandra M., Maggio, Joseph, Louis, Judith B., Atherholt, Thomas B., 2017. Occurrence and source identification of perfluoroalkyl acids (PFAAs) in the Metedeconk River Watershed, New Jersey. Environ. Sci. Pollut. Res. 24 (35), 27125–27135.

Ragnarsdóttir, Oddný, Abdallah, Mohamed Abou-Elwafa, Harrad, Stuart, 2022. Dermal uptake: An important pathway of human exposure to perfluoroalkyl substances? Environ. Pollut. 307, 119478.

Rambachan, Ashesh, Roth, Jonathan, 2023. A more credible approach to parallel trends. Rev. Econ. Stud. rdad018.

Romalino, Carly Q., 2014. Paulsboro site among n.j's worst water polluters. https://www.courierpostonline.com/story/news/local/south-jersey/2014/06/19/paulsboro-refinery-among-states-worst-water-polluters/10862763/. (Accessed 23 January 2024).

Shane, Hillary L., Baur, Rachel, Lukomska, Ewa, Weatherly, Lisa, Anderson, Stacey E., 2020. Immunotoxicity and allergenic potential induced by topical application of perfluorooctanoic acid (PFOA) in a murine model. Food Chem. Toxicol. 136.

Shapiro, Joseph S., Walker, Reed, 2021. Where is pollution moving? Environmental markets and environmental justice. In: AEA Papers and Proceedings, vol. 111, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, pp. 410–414.

Smith, V. Kerry, Huang, Ju-Chin, 1995. Can markets value air quality? A meta-analysis of hedonic property value models. J. Political Econ. 103 (1), 209–227.

Tang, Chuan, Czajkowski, Jeffrey, Heintzelman, Martin D, Li, Minghao, Montgomery, Marilyn, 2020. Rail accidents and property values in the era of unconventional energy production. J. Urban Econ. 120, 103295.

Tang, Chuyang Y., Fu, Q. Shiang, Robertson, A.P., Criddle, Craig S., Leckie, James O., 2006. Use of reverse osmosis membranes to remove perfluorooctane sulfonate (PFOS) from semiconductor wastewater. Environ. Sci. Technol. 40 (23), 7343–7349, PMID: 17180987.

Tessum, Christopher W., Paolella, David A., Chambliss, Sarah E., Apte, Joshua S., Hill, Jason D., Marshall, Julian D., 2021. PM2.5 polluters disproportionately and systemically affect people of color in the United States. Sci. Adv. 7 (18).

United States Environmental Protection Agency, 2009. Provisional health advisories for perfluorooctanoic acid (PFOA) and perfluorooctane sulfonate (PFOS). https://www.epa.gov/sdwa/drinking-water-health-advisories-pfoa-and-pfos. (Accessed 9 January 2023).

United States Environmental Protection Agency, 2023a. Monitoring Unregulated Drinking Water Contaminants. U.S. EPA, https://www.epa.gov/dwucmr/learn-about-unregulated-contaminant-monitoring-rule. (Accessed 28 November 2022).

United States Environmental Protection Agency, 2023b. Fact sheet: 2010/2015 PFOA stewardship program. https://www.epa.gov/assessing-and-managing-chemicals-under-tsca/fact-sheet-20102015-pfoa-stewardship-program. (Accessed 18 January 2024).

United States Environmental Protection Agency, 2023c. PFAS analytic tools. https://echo.epa.gov/trends/pfas-tools. (Accessed 14 March 2023).

United States Environmental Protection Agency, 2023d. Pre-publication federal register notice: PFAS primary drinking water regulation. https://www.epa.gov/system/files/documents/2023-03/Pre-Publication%20Federal%20Register%20Notice_PFAS%20NPDWR_NPRM_Final_3.13.23.pdf. (Accessed 14 March 2023).

United States Environmental Protection Agency, 2023e. Proposed PFAS national primary drinking water regulation. https://www.epa.gov/sdwa/and-polyfluoroalkyl-substances-pfas. (Accessed 14 March 2023).

USEPA, 2022. PFAS master list of PFAS substances. U.S. environmental protection agency. https://comptox.epa.gov/dashboard/chemical_lists/pfasmaster. (Accessed 9 January 2023).

USEPA, 2024. Final PFAS national primary drinking water regulation. https://www.epa.gov/sdwa/and-polyfluoroalkyl-substances-pfas. (Accessed 10 April 2024).

Wang, Zhanyun, DeWitt, Jamie C., Higgins, Christopher P., Cousins, Ian T., 2017/03/07. A never-ending story of per- and polyfluoroalkyl substances (PFASs)? In: Environmental Science & Technology. Environ. Sci. Technol. 51 (5), 2508–2518.

Waterfield, Gina, Rogers, Martha, Grandjean, Philippe, Auffhammer, Maximilian, Sunding, David, 2020. Reducing exposure to high levels of perfluorinated compounds in drinking water improves reproductive outcomes: evidence from an intervention in Minnesota. Environ. Health 19 (1).

Xiao, Xin, Ulrich, Bridget A., Chen, Baoliang, Higgins, Christopher P., 2017. Sorption of poly- and perfluoroalkyl substances (PFASs) relevant to aqueous film-forming foam (AFFF)-impacted groundwater by biochars and activated carbon. Environ. Sci. Technol. 51 (11), 6342–6351.

Zhang, Jiarui, Phaneuf, Daniel J., Schaeffer, Blake A., 2022. Property values and cyanobacterial algal blooms: Evidence from satellite monitoring of inland lakes. Ecol. Econom. 199, 107481.

Zillow Group, 2021. Zillow's transaction and assessment database (ZTRAX).. https://www.zillow.com/research/ztrax/.

Zivin, Joshua Graff, Neidell, Matthew, Schlenker, Wolfram, 2011. Water quality violations and avoidance behavior: Evidence from bottled water consumption. Amer. Econ. Rev. 101 (3), 448–453.