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DISCOVERY OF 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.

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While the US Environmental Protection Agency (EPA) 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. 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-difference 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 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 reporter released results from a 2009 test conducted by the New Jersey Department of Environmental Protection (NJDEP) showing significant levels of PFAS in several drinking water systems throughout the state. The Paulsboro Water Department in southwestern New Jersey 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).[1] Shortly after the public release of 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 perception of future contamination risk and the public's distrust of the water system and local regulators.

We find that housing prices decreased by about 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

[1]Perfluorononanoic Acid, also known as heptadecafluorononanoic acid, or PFNA, is a synthetic chemical which is part of the larger class of PFAS chemicals.

Paulsboro playing a role in the effect on housing prices. Exploring the subsequent changes in neighborhood demographics in Paulsboro, we observe a large decline in households with children, who are more at risk from exposure, a decrease in renter occupied homes, and an increase in vacant homes. We also see a decrease in white applicants for new mortgages, along with an increase in Hispanic applicants, suggesting an 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).[2] 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 is differential 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 residential sorting.

This study also contributes to the rich literature on how housing markets respond to changes in

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

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), 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 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 March 2023, the EPA proposed new drinking water standards for six PFAS, including PFNA. Our findings may assist regulators in assessing the value of these proposed public drinking water standards that, if enacted, would 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 9,000 chemicals (United States Environmental Protection Agency, 2021), 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). PFAS contamination in drinking water can originate from a number of point sources, including airports, military sites, and landfills (Hu et al., 2016). However, the most significant contamination often results from the industrial production sites of these chemicals.

In this study, we focus on contamination near a chemical plant located in West Deptford, NJ, 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 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).

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, 2023c).[3] 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).

Households may avoid PFAS exposure in drinking water through filtering their water, obtaining a new water source, or moving residential locations. However, removing PFAS from drinking water at the tap can be difficult. Not all water filters are effective at removing PFAS and some may make the situation worse if not properly maintained (Herkert et al., 2020). Reverse osmosis filters are the most efficient household system for removing PFAS, but can be expensive.[4] Pitcher filters are a less expensive option, but are often less effective in removing PFAS (Lacey et al., 2023). Despite their effectiveness, whole home systems are rare because the reverse osmosis process is slow, making it difficult to meet home-wide water demand.

1.2 Early PFAS Regulation and Testing

While PFAS remain federally unregulated by the Safe Drinking Water Act at the time of writing this manuscript, New Jersey was an early adopter of testing and monitoring for several PFAS in

[3] Perfluorooctanoic acid (PFOA) and Perfluorooctane sulfonic acid (PFOS) are the most widely studied chemicals of the broader PFAS class.

[4] The average costs of 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.

a sample of water systems across the state. PFAS testing on a national scale was not conducted until 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.

PFAS testing in New Jersey initially began in the early 2000s after contamination from a chemical plant in Parkersburg, West Virginia garnered significant media coverage and regulatory attention.[5] The NJDEP first conducted broad testing in 2006 with a study of PFOA in 23 community water systems (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, a concentration of 40 ng/L was initially used as a threshold of concern for PFOA, based on end points for toxicity identified by the EPA.

Between August 2009 and February 2010, NJDEP broadened its testing, sampling at 29 CWSs throughout the state for 10 different PFAS (Post et al., 2013). PFAS were detected in 21 of the 29 CWSs, several of which were well above 40ng/L (see Figure A2). While NJDEP contacted municipalities and told them about the PFAS detection, no residents were notified and the results were not publicly released.

1.3 Timeline of Public Discovery of PFAS Contamination in New Jersey

On July 16, 2013, a reporter received the PFAS sampling results from the 2009 NJDEP study through an Open Public Records Act request, and the results were widely publicized (Carluccio,

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

2013a,b). The NJDEP sampling results revealed that the highest level of PFNA that had been reported in drinking water worldwide had been found in one of the drinking water wells at the Paulsboro Water Department (Post et al., 2013). While NJDEP did not have a health advisory level specific to PFNA at the time, the well had levels of PFNA of 96 nangograms per liter (ng/L). Follow-up testing found even higher PFNA levels in the water delivered to residents, 150 ng/L, and in the raw water, 140 ng/L (Carluccio, 2013b). These levels far exceeded the maximum contaminant level (MCL) for PFNA of 13 ng/L that was eventually adopted by the state in September 2018 (NJDEP , New Jersey Department of Environmental Protection). Because of naturally occurring radium contamination in Paulsboro's other offline wells, the water system was unable to take immediate action to reduce PFNA in drinking water supplies (Comegno, 2014). Thus, Paulsboro was widely scrutinized 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. While PFAS were detected in other water systems, the levels of individual PFAS were below EPA and NJDEP's documented thresholds of potential concern and, therefore, did not generate the same public and regulatory scrutiny.

Shortly 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). The same month NJDEP issued its first public health advisory to Paulsboro for PFNA (Comegno, 2014). The state public health advisory 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. Residents were offered free bottled water for several months until the contaminated well could be moved offline (Laday, 2014). These actions further increased public awareness of the PFAS contamination.

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-difference 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:

$$Log(Price_{pcst}) = \beta_1 Post_t \times Pauslboro_s + \gamma_s + \theta_{ct} + \mathbf{X}_{pt} + \epsilon \tag{1}$$

for property p in county c in community water system 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. In other specifications, we define treatment as properties in all water systems with any detection of PFAS, PFNA, or elevated PFAS. The specification includes CWS fixed effects, γ_s, county-year-month fixed effects, θ_{ct}, and other property-level controls, $\mathbf{X}_{pt}$ including acres and square footage. The results are robust to 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:

$$AnySale_{pcsy} = \phi_1 Post_y \times Pauslboro_s + \gamma_s + \theta_{cy} + \mathbf{X}_{py} + \epsilon \tag{2}$$

for property p in county c in community water system 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, θ_{cy}, instead of county-year-month fixed effects. For both regressions, standard errors are clustered at the community water system 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 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:

$$\begin{aligned} Log(Price_{pcst}) = &\sum_{\tau=2007}^{2012} \alpha_\tau 1\{y=\tau\} \times Treat_s + \sum_{\tau=2014}^{2018} \pi_\tau 1\{y=\tau\} \times Treat_s \\ &+ \gamma_s + \theta_{ct} + \mathbf{X}_{pt} + \epsilon \end{aligned} \tag{3}$$

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.[6] We omit the indicator for the year 2013, normalizing to zero in that year. All other variables are defined as in equation 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

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

not directly testable, our event study estimates document parallel trends in periods prior to treatment. Trends remain parallel in the pre-period under a number of alternative specifications with different sets of fixed effects.

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 in our robustness exercises. We estimate:

$$\begin{aligned} Log(Price_{pcst}) = {} & \psi_1 Post_t \times Pauslboro_s + \psi_2 Post_t \times Within\_Xkm_s \\ & + \gamma_s + \theta_{ct} + \mathbf{X}_{pt} + \epsilon \end{aligned} \tag{4}$$

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: 5km, 10km, 20km. Other variables are defined analogously to the main specification in equation 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.[7] Property characteristics used as controls include acres and square footage. 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. Tax assessor data include property transactions from 2011 to 2018. We restrict the sample to residential properties.[8] Property characteristics used as controls include total assessment and square footage.

3.2 Demographic Data

To observe 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 poverty or low income (defined as income below 200 percent of the federal poverty level), households with children 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).

[7]Non-arms length sales were identified based on sales amount code, document type, and a variable denoting intra-family transfers.

[8]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.

We exclude 5-year estimates from 2014 to 2017, because they contain values from both before and after social discovery.

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 (2007-2013) to the post period (2014-2017).

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 (CWS) service area from the NJ Department of Environmental Protection 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 A1 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 community water system (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 the smallest geography available for both the ACS and HMDA, census tract. We compare the census tract that overlaps with most of the Paulsboro CWS service area boundary with other census tracts in Gloucester County. This tract is depicted in panel (c) of Figure A1.

3.4 Newspaper Data

We collect information on the number of newspaper articles referencing PFAS in drinking water from *Access World News*. We conducted a national 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 A2). 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. There were no articles found in languages other than English using these search terms.

4 Results

4.1 Descriptive Results

Our research design leverages the sharp timing of social discovery of PFAS contamination in Paulsboro at the end of 2013. We start by documenting the impact on newspaper coverage, as a way to measure information dissemination to the public. Using data from Access World News, Panel

(a) of Figure 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. While PFAS were detected in other water systems, the levels of individual PFAS were below EPA and NJDEP's documented thresholds of potential concern and, therefore, did not generate the same public and regulatory scrutiny.[9] Figure 1 Panel (b) shows the cumulative number of articles covering PFAS detection in water systems with elevated levels of PFAS in New Jersey.[10] 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 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. The average home value in Pauslboro prior to PFAS discovery was $94,816 as compared to an average of $297,386 for homes served by other water systems in NJ. While home prices in other systems increased slightly after 2013, the average home price in Paulsboro dropped to $61,678 after the release of information about PFAS contamination. This raw comparison of means suggests that home values declined substantially in Paulsboro in response to contamination information.

[9]Figure A2 shows the level PFNA and the sum of all types of PFAS detected at water systems with any amount detected.

[10]We report articles for systems with the total sum of all tested PFAS over 50 ng/L (see Figure A2), excluding two systems that changed names during our sample period and are therefore difficult to track over time.

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 equation (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 equation (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.[11] 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 equation 2 and find little evidence of a systematic shift in the probability of homes being sold. Across specifications, we find no statistically significant changes. 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.[12] 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.

Figure 2 plots the corresponding event study style estimates from equation (3).[13] Panels (a)

[11]Table A1 shows that the main results are robust to alternate levels of clustering.

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

[13]Table A2 and Figure A3 replicate Table 2 and Figure 2a using the Gloucester County tax assessor data rather

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 A3 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.

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 lower levels of PFAS contamination may have been impacted.[14] We test for changes in property values at other water systems with some level of detected PFAS in Panel (a) of Table 3. 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

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.

[14]During the 2009 testing, water samples were collected at 29 CWSs across the state and tested for 10 different PFAS, including PFNA. Figure A2 shows the level of total PFAS (sum of the 10 PFAS tested) and level of PFNA at systems with elevated levels.

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.[15] Panel (b) reports changes in housing prices for homes served by other water systems that were very near, within 2km, 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 equation 4 and shows the change in home prices for homes served by water systems within 5km, 10km, and 20km of the chemical plant near Paulsboro. Across all distances, the effects are small in magnitude and

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

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 A4 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.

Next, Table A3 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.

Finally, 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 A5 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.

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 led to residential sorting and broader changes in neighborhood characteristics. While we cannot observe property-level demographic characteristics, we explore broader neighborhood changes in 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 the rest of Gloucester County.[16]

Before 2013, compared to the rest of the county, Paulsboro had a smaller fraction of White, non-Hispanic residents, a larger fraction of Black residents, a larger fraction of households below poverty or classified as low-income, and a larger fraction of renter-occupied households. These patterns are consistent with the broader environmental justice literature that has documented higher exposure to pollution among disadvantaged communities in the cross-section.

After 2013, the most 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, this decline was less than a 2 percentage point change. Because children are still developing, they may be more sensitive to the harmful effects of PFAS. Young children

[16] Table A4 shows similar patterns when Non-Paulsboro areas are expanded to include the entire state of NJ, rather than just Gloucester County.

also may have higher exposure to PFAS in carpets, household dust, toys, and cleaning products, because they crawl on the floor and often put things in their mouths. The large decline in 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.

Both the fraction of households below poverty and the fraction of renter-occupied households decreased in Paulsboro. 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 an increase in vacant homes. Compared to renters, homeowners typically have higher moving costs. Homeowners also experienced a large negative shock to their home value, and may have had an especially difficult time selling their homes given the negative impacts to the housing market we find in this study.[17]

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 the rest of the county.[18] We see a large decrease in White, non-Hispanic applicants for new mortgages and an increase in Hispanic applicants in Paulsboro after the contamination was discovered in 2013. While this trend is 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 demand for homes in Paulsboro decreased for White New Jersey homebuyers, and increased among Hispanic home-

[17] Across the state, property owners may have had an especially difficult time selling their homes during this time due to statewide declines in housing values stemming from the housing crisis in 2008 including a foreclosure moratorium for large loan servicers in New Jersey from late 2010 into 2011 (Collins and Urban, 2018). Nevertheless, we have no reason to expect these features to have impacted Paulsboro differently than other areas of the state and parallel pre-trends give support for this assumption.

[18] Table A5 shows similar patterns when Non-Paulsboro areas are expanded to include the entire state of NJ, rather than just Gloucester County.

buyers. However, we do not see increases in lower-income mortgage applicants. The increase in 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 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 42 percent on average after social discovery of contamination for properties within the Paulsboro water system service area relative to other properties within Gloucester County and across the state. This decline was concentrated in 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 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 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 July 2013 through February 2014, we observe the negative effects on housing values were sustained through 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 other environmental hazards may have led to increasing distrust of the local government in Paulsboro and may have set the stage for these large effects. For example, in November 2012, a train derailment caused the release of vinyl chloride into the air (Mulvihill, 2012). While the vinyl chloride spill did not contaminate Paulsboro's drinking water supply and we do not observe a drop in housing prices in Paulsboro immediately after the spill, this incident may have contributed to the deteriorating reputation of environmental quality in the community (Forand, 2014).

Our estimate of a 42 percent decrease in property values represents a change in value of about \$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 27-43% (Christensen et al., 2023). In terms of total valuation, the PFAS contamination in Paulsboro led to a decline of about $46 million.[19]

The decline in property values in Paulsboro was accompanied by changes in neighborhood demographics in Paulsboro. Large declines in households with children may reflect the greater risk of harm to children from exposure to PFAS. We also document a decrease in renter occupied households and an increase in vacant homes. 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 decrease in white applicants for new mortgages, along with an increase in 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 can 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 March 2023 proposal to set federal drinking water standards for PFAS that are lower than all existing PFAS standards. The proposed rule would require systems to monitor, notify the public, and remediate if the proposed standards are violated (United States Environmental Protection Agency, 2023d). 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.

[19]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.

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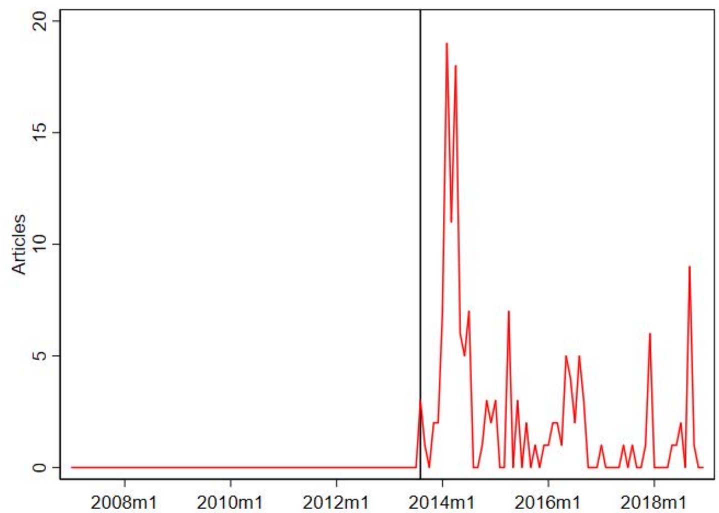
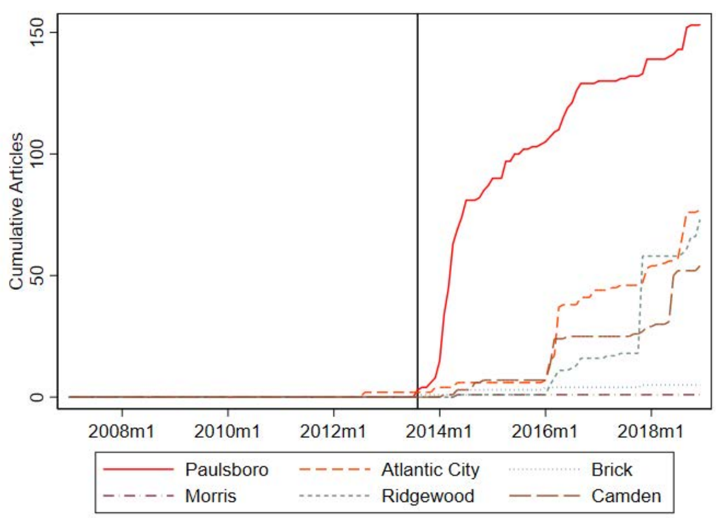
6 Figures

Figure 1: News Articles on PFAS



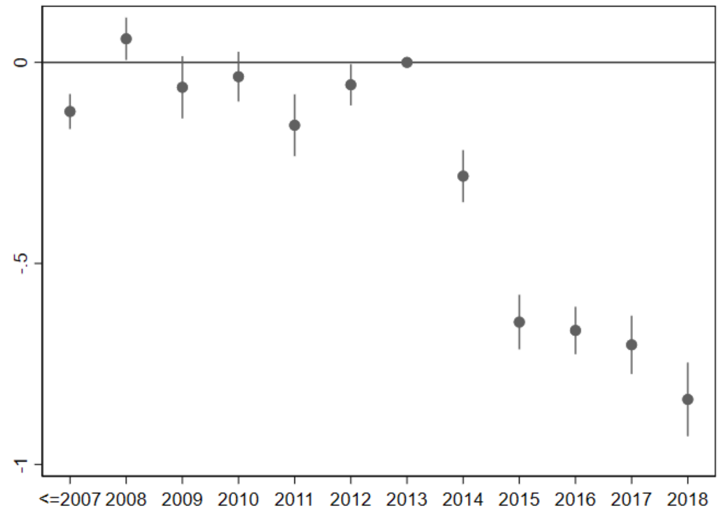
(a) Paulsboro Articles per Month



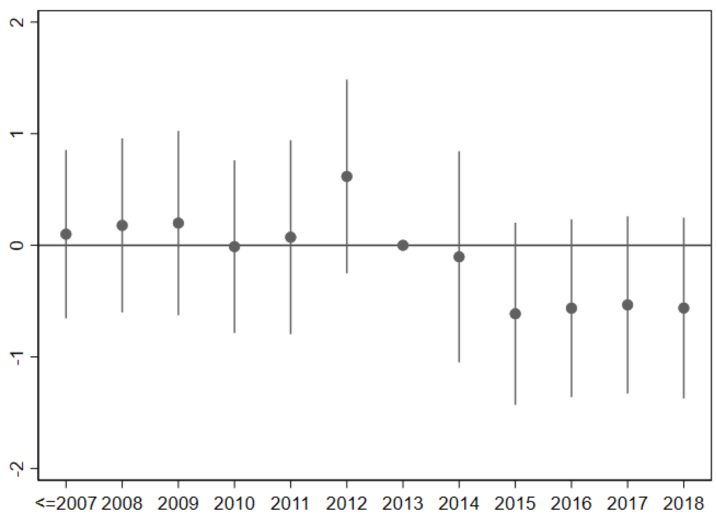
(b) Cumulative Articles for Systems with PFAS

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 A2. 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.

Figure 2: Effect on Log(House Prices) in Paulsboro



(a) CWS fixed effects



(b) Property fixed effects

Note: Figure plots results from estimation of equation 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).

7 Tables

Table 1: Mean Housing Prices

	Community Water System		
	Non-Paulsboro	Paulsboro	Total
	(1)	(2)	(3)
Before 2013	\$297,386	\$94,816	\$297,173
	(\$186,939)	(\$60,550)	(\$186,966)
After 2013	\$307,476	\$61,678	\$307,259
	(\$204,607)	(\$59,448)	(\$204,654)
Total	\$299,953	\$87,435	\$299,739
	(\$191,640)	(\$61,844)	(\$191,672)

Note: Table reports mean home values and standard deviations in parentheses for residential homes served by community water systems from 2000-2018 using ZTRAX data. Columns (1)-(3) show average home prices for homes served by water systems other than Paulsboro, homes served by Paulsboro water system, and all homes. The first row shows mean home prices in 2013 and earlier, while the second row shows mean home prices after 2013. The final row shows overall mean home prices.

Table 2: Effect on Home Sales in Paulsboro

	(1)	(2)	(3)	(4)	(5)
			Panel A. Log(House Price)		
Post × Paulsboro	-0.541***	-0.561***	-0.558***	-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	0.536	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	19,036,796	17,509,104	17,509,104	17,509,104	19,036,767
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 equation 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.

Table 3: Effects on Other Systems

	(1)	(2)	(3)
Panel A. Other Systems with Detected PFAS			
Post × Paulsboro	-0.576***	-0.484***	-0.545***
	(0.0408)	(0.0622)	(0.0497)
Post × Any PFAS	0.0149		
	(0.0338)		
Post × Any PFNA		-0.0771	
		(0.0579)	
Post × Elevated PFAS			-0.0167
			(0.0440)
Panel B. Other Systems Near PFAS Facilities			
Post × Paulsboro	-0.569***	-0.561***	-0.584***
	(0.0333)	(0.0231)	(0.0303)
Post × Near Any Site	0.00847		
	(0.0265)		
Post × Near Fed Site		-0.0216	
		(0.0781)	
Post × Near PFAS Producerd			0.0246
			(0.0213)
Panel C. Spatial Spillovers			
Post × Paulsboro	-0.567***	-0.575***	-0.563***
	(0.0674)	(0.0346)	(0.0233)
Post × Within 5km	0.00715		
	(0.0704)		
Post × Within 10km		0.0270	
		(0.0452)	
Post × Within 20km			0.0323
			(0.0412)
Observations	1,352,418	1,352,418	1,352,418
R-squared	0.536	0.536	0.536

Note: Table reports regression results estimating equation 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), $Within\ 5km$, $Within\ 10km$, and $Within\ 20km$ 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.

Table 4: ACS: Changes in Demographics in Gloucester

	Non-Paulsboro		Paulsboro	
	Pre-2013	Post-2013	Pre-2013	Post-2013
White, non-Hispanic	82.47	78.91	55.45	55.46
Black, non-Hispanic	8.96	9.22	33.97	29.09
Hispanic	4.48	6.55	5.82	8.98
Low Income	18.71	17.93	41.78	37.45
Below Poverty Rate	7.77	7.81	23.37	14.81
Children under 18	23.47	21.66	30.19	16.45
Households				
Children under 18	36.71	33.24	39.19	22.73
Vacant Homes	5.41	6.78	10.82	17.83
Renter-Occupied Homes	18.57	19.86	40.19	27.96

Note: Table reports summary statistics by Census Tract from American Community Survey (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 A1. Non-Paulsboro consists of all other Census Tracts in Gloucester County, New Jersey.

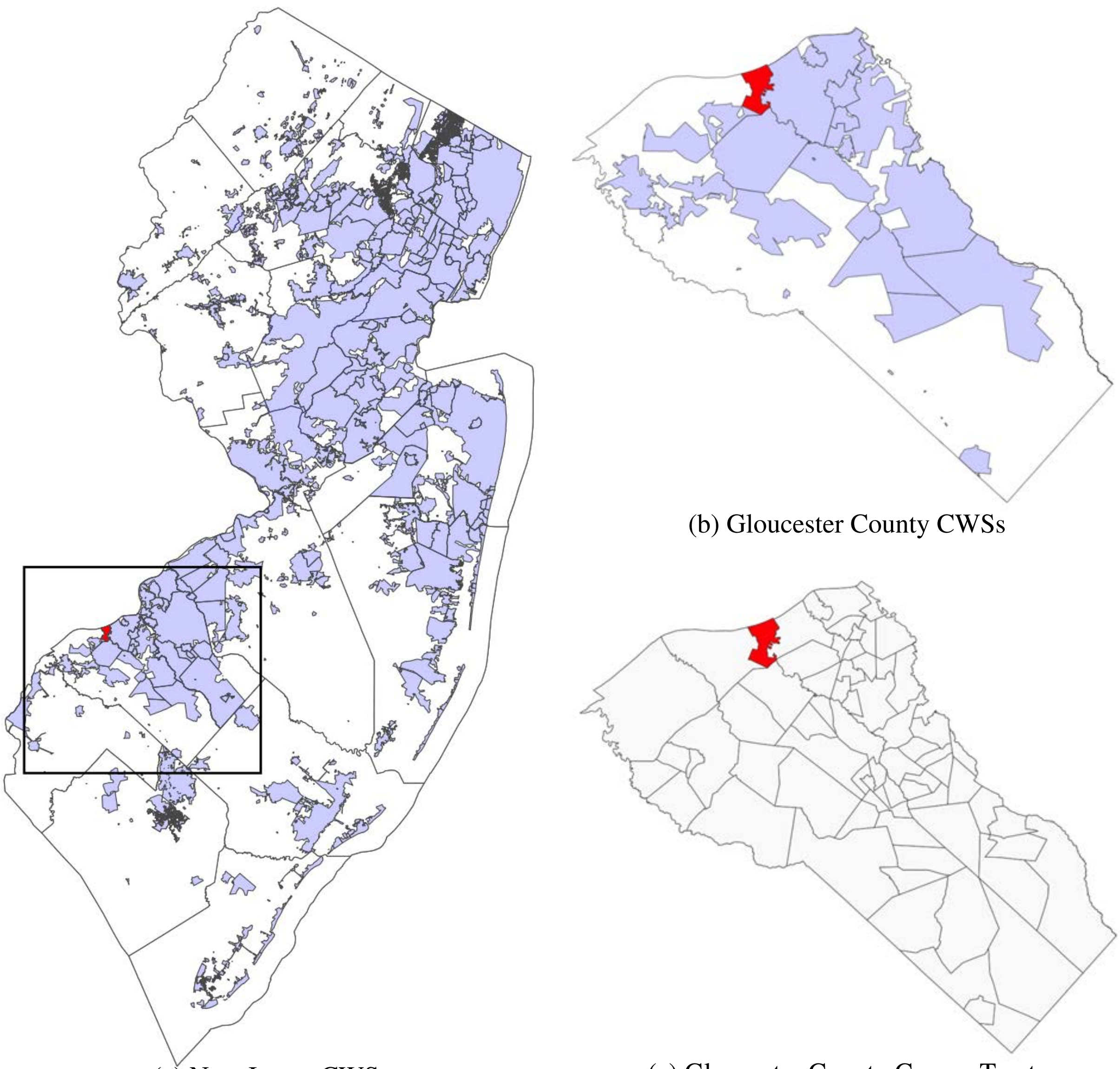
Table 5: HMDA: Characteristics of Mortgage Applications in Gloucester

	Non-Paulsboro		Paulsboro	
	Pre-2013	Post-2013	Pre-2013	Post-2013
White, non-Hispanic	81.36	79.72	71.83	59.81
Black, non-Hispanic	5.10	6.55	14.92	15.05
Hispanic	3.15	4.18	5.85	13.70
Log(Loan Amount)	12.09	12.08	11.61	11.50
Log(Applicant Income)	11.21	11.27	10.76	10.83
Percent Income over 70k	51.15	56.54	14.03	17.37

Note: Table reports summary statistics of mortgage applicants from Home Mortgage Disclosure Act (HMDA) data.

Online Appendix

Figure A1: CWS Service Area and Census Tract Boundaries



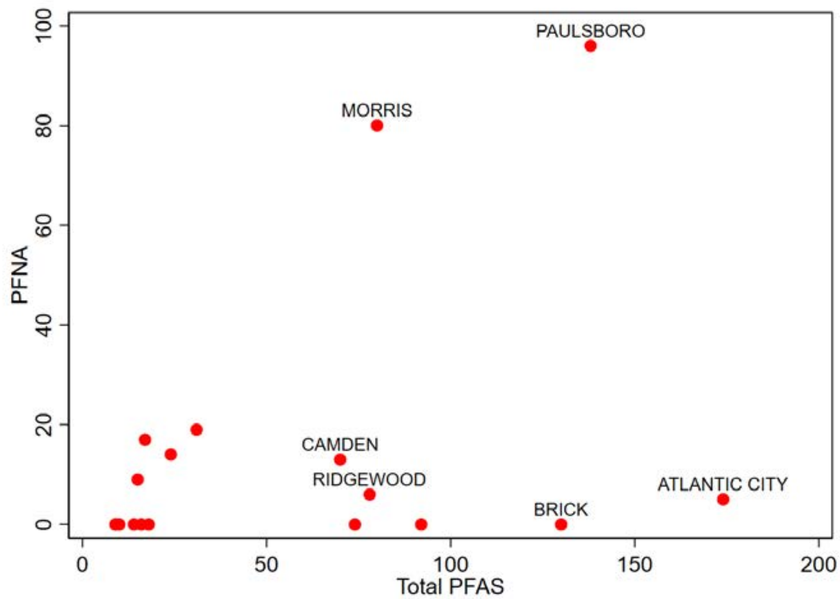
(a) New Jersey CWSs

(b) Gloucester County CWSs

(c) Gloucester County Census Tracts

Note: Figure depicts Community Water System (CWS) service area boundaries for the full state of New Jersey in panel (a) and just Gloucester County in panel (b). Panel (c) depicts Census Tract boundaries in Gloucester County. The boundary for the Paulsboro CWS is darkened in both figures (a) and (b). The boundary for the Census Tract that comprises most of the Paulsboro CWS is darkened in panel (c).

Figure A2: Level of PFNA and Total PFAS Detected



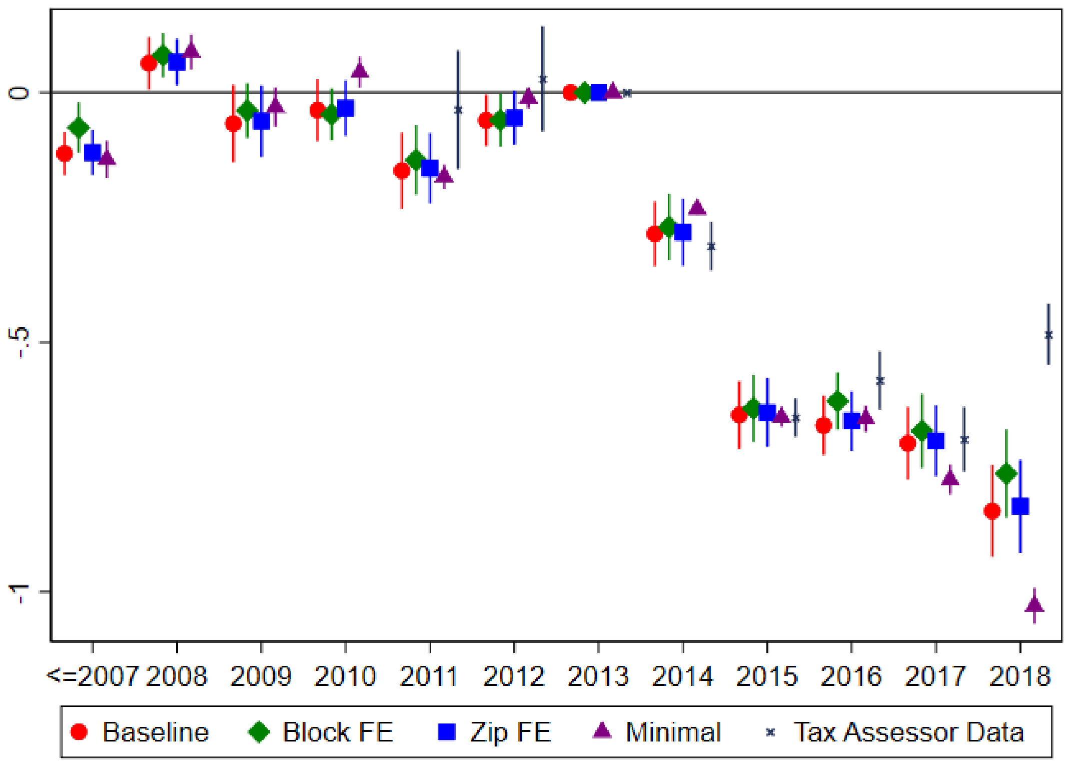
Note: Figure shows the level of PFNA detected on the y-axis and the sum total of all types of PFAS detected on the x-axis for any systems with positive detection. Full CWS names of the named systems in the Figure above (from highest to lowest Total PFAS) include Atlantic City MUA, Paulsboro Water Department, Brick Township MUA, Southeast Morris County MUA, Ridgewood Water, and Camden City Department of Public Works. The two systems with PFAS detections above 50 ng/L that are not named in the Figure and not included in Figure 1b changed their name during our sample: Suez Water New Jersey - Birch Hill (formerly West Milford MUA - Birch Hill) and NJ American Water Co. - Raritan (formerly NJ American Elizabethtown-Netherwood Wellfield). While Southeast Morris County MUA also was found to have high PFNA in the 2009 NJDEP study, "PFNA was not detected in a followup sample" while a follow up study at Paulsboro detected even higher levels of PFNA (Post et al., 2013).

Table A1: Robustness to Level of Clustering

	(1)	(2)	(3)	(4)	(5)
Post × Paulsboro	-0.561***	-0.561***	-0.561***	-0.561***	-0.561***
	(0.0568)	(0.0893)	(0.0213)	(0.0231)	(0.00117)
Observations	1,352,418	1,352,418	1,352,418	1,352,418	1,352,418
R-squared	0.536	0.536	0.536	0.536	0.536
County-year-month FE	yes	yes	yes	yes	yes
CWS FE	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes
Cluster	Property	Blk group	Zip code	PWS	County

Note: Table reports regression results estimating equation 1 using ZTRAX data from 2000-2018. The outcome is the log of sales price. The sample includes residential homes served by a CWS. $Post$ equals one if the home is sold after August 2013 and $Paulsboro$ equals one if the property is located within the Paulsboro CWS service area. All columns include county-by-year-by-month and CWS fixed effects, as well as controls for acres and square footage. Standard errors are clustered at the property, block group, zip code, CWS, and county level in columns (1)-(5), respectively.

Figure A3: Robustness to Alternative Specifications and Data



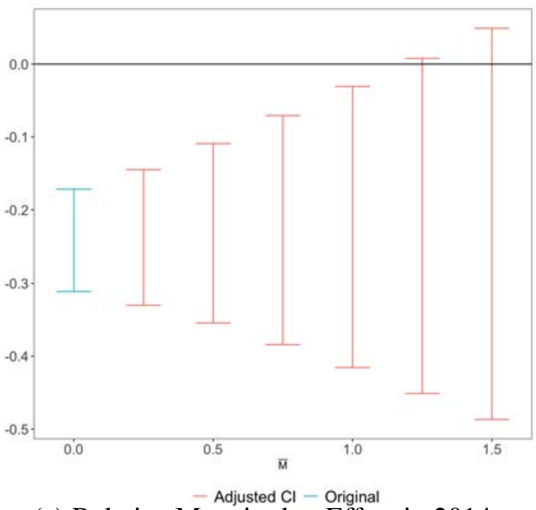
Note: Figure plots results from estimation of equation 3 and the outcome is the log of sales price. The sample includes residential homes served by a CWS. The omitted reference year is 2013. Standard errors are clustered at the CWS level. The baseline specification is depicted with circles. Estimates depicted with a diamond and square additionally control for block group and zip code fixed effects, respectively. Estimates depicted with a triangle include only year and CWS fixed effects, dropping county-by-year-by-month fixed effects from the baseline specification. Estimates depicted with an X estimate the baseline specification using Gloucester county tax assessor data.

Table A2: Tax Assessor Data: Effect on Log(House Prices) - Paulsboro

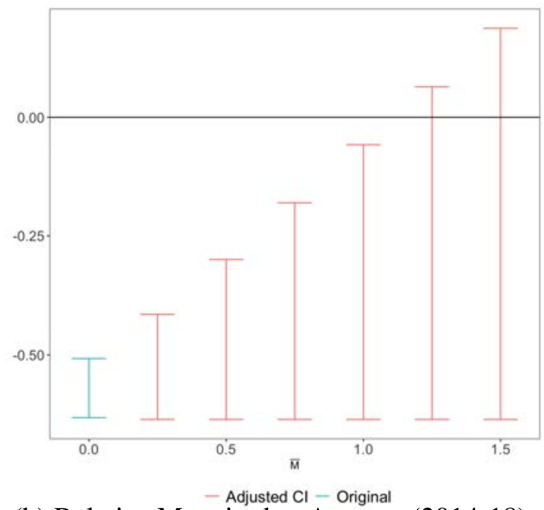
	(1)	(2)	(3)	(4)	(5)
Post × Paulsboro	-0.574***	-0.569***	-0.571***	-0.541***	-0.217***
	(0.0306)	(0.0339)	(0.0341)	(0.0319)	(0.0609)
Observations	12,872	12,872	12,871	12,864	4,219
R-squared	0.230	0.492	0.497	0.529	0.774
County-year-month FE	yes	yes	yes	yes	yes
CWS FE	yes	yes	yes	yes	
Controls		yes	yes	yes	
Zip FE			yes		
Blk group FE				yes	
Property FE					yes

Note: Table reports regression results estimating equation 1 using Gloucester county tax assessor data from 2011-2018. The outcome is the log of sales price. The sample includes residential homes served by a CWS. $Post$ equals one if the home is sold after August 2013 and $Paulsboro$ equals one if the property is located within the Paulsboro CWS service area. Columns (1)-(4) include county-by-year-by-month and CWS fixed effects, column (2) adds controls for total assessment and square footage, column (3) adds zip code fixed effects, while column (4) adds block group fixed effects. Column (5) includes county-by-year-by-month and property level fixed effects. Standard errors are clustered at the CWS level.

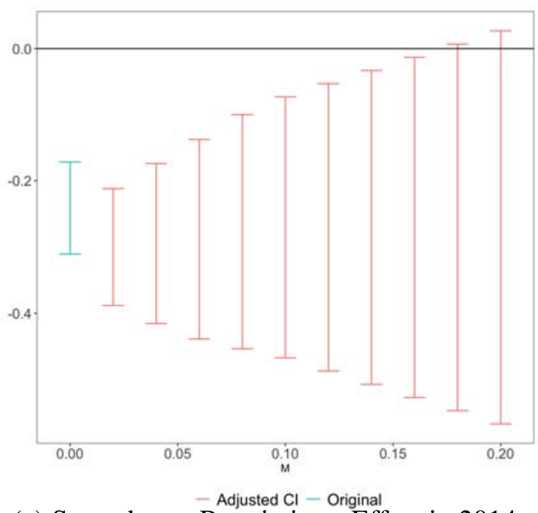
Figure A4: Robustness to Violations in Parallel Trends



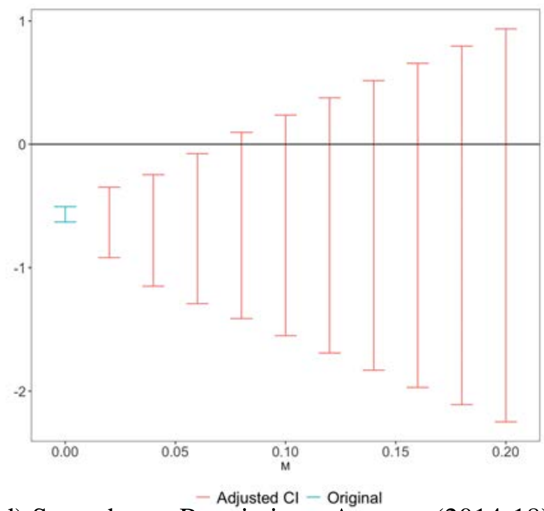
(a) Relative Magnitude - Effect in 2014



(b) Relative Magnitude - Average (2014-18)



(c) Smoothness Restriction - Effect in 2014



(d) Smoothness Restriction - Average (2014-18)

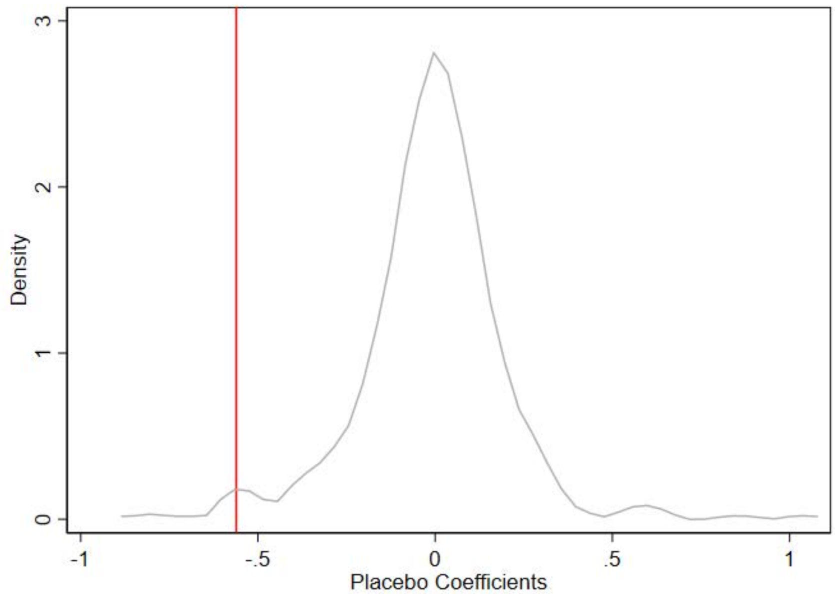
Note: Figure plots results from the Rambachan and Roth (2023) approach to test the sensitivity of DiD results to violations in parallel trends. The sample includes ZTRAX data from 2007 to 2018, with 2013 denoted as the treatment year. Panel (a) focuses on the first post period, 2014, while Panel (b) uses the average of the post period (2014-2018). 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. The blue band ("Original") is the 95% confidence interval of the standard DiD treatment effect estimate. The red bands ("Adjusted CI") report the robust confidence intervals as we vary $\bar{M}$. The breakdown value for $\bar{M}$ is about 1.25, which means the results are robust to violations of parallel trends in the post period up to 1.25 times as large as the maximum violation in the pre-treatment period. Panels (c) and (d) depict sensitivity of results to non-linearity for the effect in 2014 in Panel (c) and the average post-period effect in Panel (d). 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 statistically significant for non-linearity associated with a fairly large change in the slope of the differential trend.

Table A3: Effect on Log(House Prices) - Robustness

	(1) Baseline	(2) Any Price	(3) Price $< 1m$	(4) Price $> 1k$	(5) Include non-residential	(6) Include non-PWS	(7) Exclude any PFAS
Panel A. Ztrax (full sample)							
Post × Paulsboro	-0.561***	-0.593***	-0.580***	-0.574***	-0.505***	-0.580***	-0.562***
	(0.0231)	(0.0240)	(0.0240)	(0.0231)	(0.0240)	(0.0732)	(0.0231)
Observations	1,352,418	1,397,293	1,359,148	1,390,563	1,376,620	1,500,989	998,738
R-squared	0.536	0.501	0.466	0.568	0.484	0.623	0.532
Panel B. Ztrax (2011-2018, Gloucester county only)							
Post × Paulsboro	-0.581***	-0.620***	-0.609***	-0.593***	-0.540***	-0.532***	-0.581***
	(0.0287)	(0.0300)	(0.0301)	(0.0287)	(0.0283)	(0.102)	(0.0287)
Observations	15,283	15,382	15,313	15,352	18,507	17,797	15,283
R-squared	0.336	0.299	0.311	0.321	0.352	0.368	0.336
Panel C. Tax Assessor (2011-2018, Gloucester county only)							
Post × Paulsboro	-0.569***	-1.055***	-1.038***	-0.581***	-0.547***	-0.553***	-0.569***
	(0.0339)	(0.0694)	(0.0630)	(0.0247)	(0.0300)	(0.0381)	(0.0339)
Observations	12,872	14,839	14,834	12,877	14,452	16,484	12,872
R-squared	0.492	0.114	0.117	0.464	0.364	0.475	0.492
Controls	yes	yes	yes	yes	yes	yes	yes
County-year-month FE	yes	yes	yes	yes	yes	yes	yes
CWS FE	yes	yes	yes	yes	yes		yes
Block grp FE						yes	

Note: Table reports regression results from estimating equation 1. Panel (a) uses ZTRAX data from 2000-2018 from all of NJ, Panel (b) uses ZTRAX data from 2011-2018 from Gloucester county only, and Panel (c) uses Gloucester county tax assessor data from 2011-2018. The outcome is the log of sales price. $Post$ equals one if the home is sold after August 2013 and $Paulsboro$ equals one if the property is located within the Paulsboro CWS service area. Standard errors are clustered at the CWS level. Column (1) replicates the baseline specification with county-year-month, CWS fixed effects, and controls for each data sample in Panels (a)-(c). Column (2) includes price outliers (above $1 million and below $1,000), column (3) restricts only to prices below $1 million, and column (4) restricts only to prices above $1,000. Column (5) includes non-residential properties. Column (6) includes properties outside community water system boundaries and includes block group fixed effects rather than CWS fixed effects. Column (7) excludes any properties served by a CWS with any detected level of PFAS.

Figure A5: Randomization Inference: Effect on Log(House Prices)



Note: Figure plots the distribution of placebo point estimates from randomizing treatment across community water systems throughout the state. The vertical line denotes the main point estimate from the treatment effect estimated for Paulsboro. The "randomized inference p-value" is 0.027.

Table A4: ACS: Changes in Demographics

	Non-Paulsboro		**Paulsboro**	
	Pre-2013	Post-2013	Pre-2013	Post-2013
White, non-Hispanic	58.99	54.43	55.45	55.46
Black, non-Hispanic	14.62	13.87	33.97	29.09
Hispanic	17.15	20.32	5.82	8.98
Low Income	24.00	23.82	41.78	37.45
Below Poverty Rate	10.39	10.65	23.37	14.81
Children under 18	23.18	21.65	30.19	16.45
Households				
Children under 18	35.76	33.03	39.19	22.73
Vacant Homes	9.21	9.16	10.82	17.83
Renter-Occupied Homes	35.15	37.12	40.19	27.96

Note: Table reports summary statistics by Census Tract from American Community Survey (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 A1. Non-Paulsboro consists of all other Census Tracts in New Jersey.

Table A5: HMDA: Characteristics of Mortgage Applications

	Non-Paulsboro		**Paulsboro**	
	Pre-2013	Post-2013	Pre-2013	Post-2013
White, non-Hispanic	57.39	55.13	71.83	59.81
Black, non-Hispanic	10.19	10.14	14.92	15.05
Hispanic	13.41	15.80	5.85	13.70
Log(Loan Amount)	12.35	12.38	11.61	11.50
Log(Applicant Income)	11.40	11.45	10.76	10.83
Percent Income over 70k	63.54	66.41	14.03	17.37

Note: Table reports summary statistics of mortgage applicants from Home Mortgage Disclosure Act (HMDA) data.