Economic Impact of PFAS Contamination: Evidence from Residential Property Values

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Abstract

We quantify the economic effects of drinking water contamination with per- and polyfluoroalkyl substances (PFAS) on the housing market. Using the EPA's Third Unregulated Contaminant Monitoring Rule (UCMR3) national PFAS reports and residential property transactions data, we apply Difference in Differences (DiD) hedonic models to assess the impact of PFAS contamination on residential property values in Harrisburg, PA. We verify the assumptions required for the DiD model and pay particular attention to spatial spillover effects. We observe intricate spillover effect dynamics, wherein properties nearest to, but outside of, the contaminated area decrease in value after PFAS contamination is detected in the drinking water of an adjacent public water system (PWS). On the other hand, market values increase for properties that are further than one but within two miles from the boundary of the affected PWS. Accounting for the spillover effect, the DiD results show that properties serviced by the affected PWS lose $10,000 in market value. This estimate is robust to various specifications, including several different spatial fixed effects, alternative treatment and control group arrangements, propensity score matching, and placebo tests.

Key words: PFAS, Drinking Water, Hedonic Model, DiD, Spillover Effect.

JEL: Q25, Q51, Q53, R31

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Introduction

Per- and Polyfluoroalkyl substances (PFAS) include more than ten thousand synthetic chemicals that have been used extensively for their water, grease, heat, and stain-resistant properties since the early 1940s (EPA 2024a; Glüge et al. 2020). However, the evidence for significant negative environmental and public health impacts has been steadily mounting (Andersson et al., 2019; Beans, 2021; Cathey et al., 2023; CDC, 2022; Steenland et al., 2010). Health effects of exposure to PFAS include cancer, high cholesterol, hypertension, and kidney disease among others (CDC 2022; Kim et al. 2018). Despite the ubiquity of PFAS in industrial production and household consumption and the associated environmental and human health impacts, the economic magnitude of the externality has not been assessed.

Drinking water is the primary route for human exposure to PFAS in the contaminated communities (De Silva et al. 2021). Yet, PFAS have not been regulated under the Safe Drinking Water Act (SDWA), and until recently, there has been no mandate for public water supply systems (PWS) to monitor and control these substances in drinking water. The severity of PFAS drinking water contamination impacts on human health was broadly recognized relatively recently. Consequently, the EPA issued and revised the PFAS Health Advisories (HAs) in 2009, 2016, and 2022[3]. In April 2024, the EPA finalized the National Primary Drinking Water

[3] The 2009 and 2016 advisories included Perfluorooctane sulfonic acid (PFOA) and Perfluorooctanoic acid (PFOS). The 2022 HA added Perfluorobutane sulfonate (PFBS), and Hexafluoropropylene Oxide Dimer Acid and its Ammonium Salt (GenX) (EPA 2009; EPA 2022; EPA 2023). The 2009 PFOA and PFOS HA thresholds for public health risk were 400 ppt (part per trillion) and 200 ppt. In 2016 and 2022the guidelines were lowered to 70 ppt for both and to 0.04 and 0.02 ppt, respectively.

Regulations (NPDWR) for six types of PFAS[4]. The NPDWR mandates all PWSs to keep PFAS below maximum concentration levels (MCLs) starting from 2029.

The EPA relies on the Unregulated Contaminated Monitoring Rule (UCMR) program to collect data on suspected drinking water contaminants that are not regulated under the SDWA. The third UCMR (2013-2016) tested all large and a subset of small PWSs for drinking water contamination with six types of PFAS and detected at least one type of PFAS in 4.04% (n=193) of PWSs in 121 counties and 33 states (EPA 2017; Hu et al. 2016; Khanal and Elbakidze 2024)[5] . UCMR3 data is the earliest nationally consistent PFAS testing effort. However, additional PFAS data have been collected in some jurisdictions and used for assessment of exposure through drinking water (Andrews and Naidenko 2020; Cadwallader et al. 2022; Smalling et al. 2023).

Drinking water PFAS contamination can result in residential sorting as it encourages households that rely on drinking water from the affected PWSs to relocate and discourages new households from moving to the contaminated areas (Banzhaf and Walsh 2008). This avoidance behavior results in deflated real estate property values in the affected areas. We quantify this economic effect using hedonic property valuation and an empirical strategy involving various Difference in Differences (DiD) specifications. In our setting, PFAS contamination of public drinking water supply is expected to decrease demand and increase willingness to sell properties in the affected localities.

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[4] The NPDWR set legally enforceable restrictions called Maximum Contaminant Level (MCLs) for Perfluorooctane sulfonic acid (PFOA) and Perfluorooctanoic acid (PFOS), Perfluorononanoic acid (PFNA), and Hexafluoropropylene Oxide Dimer Acid and its Ammonium Salt (GenX/HFPO-DA), Perfluorohexanesulphonic acid (PFHxS), and mixture of two or more of PFNA, PFHxS, HFPO-DA, and PFBS (US EPA 2024).

[5] UCMR5 (2023-2026) is testing 29 types of PFAS in all large and a subset of small PWSs in the US and its territories (EPA 2024b).

The hedonic property value model is widely used for assessing the economic impacts of environmental externalities on the real estate market (Banzhaf 2021; Brasington and Hite 2005; Christensen, Keiser and Lade 2023; Currie et al. 2015; Greenstone 2017; Greenstone and Gallagher 2008). The DiD models have been used extensively in hedonic studies to establish causality and rely on the availability of suitable treatment and control group pre and post treatment data (Abadie and Cattaneo 2018; Banzhaf 2021; Cameron and Trivedi 2005; Currie et al. 2015; Greenstone 2017). In our setting, the DiD model contrasts prices of homes serviced by the contaminated (treatment) and non-contaminated (control) PWSs before and after discovery of water contamination. The objective is to isolate the effect of drinking water PFAS contamination on the price trajectory of homes located in the affected PWS.

The causal inference in DiD relies on important assumptions, including (i) parallel trends of property prices in treatment and control groups in the absence of treatment ; (ii) similarity of property attributes in treatment and control groups except for the treatment status; and (iii) no treatment spillovers to the control group so that only properties in the treatment group are affected by the treatment (Abadie and Cattaneo 2018; Athey and Imbens 2017; Cameron and Trivedi 2005). Visual examination of the data and matching DiD models are commonly used to account for some of these assumptions (Anica and Elbakidze 2023; Banzhaf 2021; Bennear and Olmstead 2008; Christensen et al. 2023; Keiser and Shapiro 2019). We explicitly account for these assumptions by evaluating a battery of DiD specifications with carefully designed combinations of treatment and control groups. We test parallel trends of treatment and control home prices before treatment, account for the spillover effect using spatial buffer rings, and use propensity score matching and placebo test for robustness check.

The results show that treatment spillover is present up to two miles from contaminated PWS boundary. Prices of homes within one mile from the border of affected PWS decline, while prices of homes located between one- and two-miles buffer increase relative to the homes located farther than two miles from the contaminated PWS. The depreciation of home prices within one mile of the contaminated PWS is due to the spillover avoidance behavior. The appreciation of values in the one to two miles buffer is due to increased demand for those properties by buyers who prefer to live close to downtown Harrisburg but wish to avoid potential exposure to PFAS.

Correcting for the spillover effect, we find that values of homes serviced by contaminated PWS decline by $9,000 to $13,000 following the discovery of PFAS. The cumulative loss in single family residential home values in Dauphin County is between $251 and $363 million. We also investigate the heterogeneity of the impact across property size and age. We find that newer and larger homes experience greater price declines due to PFAS contamination than smaller and older houses. All estimates remain robust in various combinations of year, municipality, PWS, and school district fixed effects. Propensity score matching and placebo test regressions also confirm the results.

We contribute to prior literature on the implications of drinking water contamination for residential property values by quantifying the effect for PFAS, which have been detected in drinking water supplies of numerous communities in the US (Hu et al. 2016; Khanal and Elbakidze 2024). Prior studies have investigated the impact of public water supply led contamination (Christensen et al., 2023), groundwater petroleum contamination (Guignet et al. 2018), unconventional oil and gas fracking (Muehlenbachs, Spiller and Timmins 2015), and trichloroethylene waste (McLaughlin 2011) on residential property prices. PFAS contamination differs from these pollutants because these chemicals are not regulated under the SDWA but have been detected in many communities' drinking water. Hence, most PWSs have not invested in removal of PFAS from drinking water supplies, which implies that properties that rely on public water supply have not been shielded from PFAS contamination. No nationally consistent data is available on the exposure of private drinking water wells to PFAS.

We also provide a detailed illustration of the spillover effect where prices of properties adjacent to the treatment group are affected negatively or positively depending on the proximity to the boundary of the contaminated PWS. These spillover effects imply that DiD estimates can include positive and negative biases, which may or may not cancel, unless the properties affected by the spillover are excluded from DiD estimation.

Empirical Strategies

We take advantage of the variation in home sale prices across time and space to estimate the effect of drinking water PFAS contamination on the housing market. We rely on several DiD specifications, including a matched DiD, as well as a placebo test, and event study-based test for the pre-treatment parallel trend. We also assess the spillover effects and use corresponding control groups with spatial buffers in our preferred DiD model to estimate the impact of PFAS contamination on the housing market.

Difference in differences

Randomized treatment data are rare in observational social science studies. In environmental economics, the impacts of contamination are commonly examined using non-randomized treatment data and DiD techniques (Athey and Imbens 2017; Banzhaf 2021; Bishop et al. 2020). We use DiD hedonic price models to infer causal impact of drinking water PFAS contamination on the housing market. The DiD strategy relies on the comparison of outcomes across treatment and control groups before and after the treatment. The strategy mimics an experimental design and can be used to produce causal estimates if properties are comparable in the treatment and control groups, the parallel trend assumption holds, and no spatial treatment spillover effect is present (Cameron and Trivedi 2005; Roth et al. 2023; Sinclair, McConnell and Green 2012).

In our setting, the treatment group includes all single-family residential house transactions within the contaminated PWS service boundary. The control group includes various combinations of transactions outside the contaminated PWS but within the same county boundary. The contaminated PWS is identified using EPA's UCMR3, which reported five types of PFAS in the affected PWS in Harrisburg in February 2014. The discovery was also reported by the Department of Air Force (DAF 2021).

The DiD model expresses home prices as a function of observable house characteristics, drinking water PFAS contamination status, and unobservable neighborhood factors. Our baseline model is provided in equation (1), where P_{igt} is the price of house i sold in neighborhood g in year t, $\boldsymbol{H}_{igt}$ is the vector of observed house characteristics, C_{igt} is the treatment group indicator with 1 if transaction is from contaminated PWS and 0 otherwise, and Γ is a binary pre (0) versus post (1) treatment year (2014) indicator. ψ_g is the neighborhood fixed effect for school district, PWS, or township depending on the model specification. Time varying unobserved effects are controlled using year FE, τ_t. The parameter of interest is β_4, which represents the difference in prices of treatment and control transactions before and after treatment. We use several specifications of DiD depending on control groups (treatment group is same for all specifications), that include all transactions outside the contaminated PWS in Dauphin County, all transaction in Dauphin County outside the contaminated PWS and the two-miles buffer around the contaminated PWS, and transaction in Cumberland County. All specifications exclude transaction of homes that depend on private drinking water wells[6].

$$P_{igt} = \boldsymbol{\beta_1 H_{igt}} + \beta_3 C + \beta_4\, \Gamma * C + \psi_g + \tau_t + \mu_{it} \dots\dots..(1)$$

Parallel Trend

One of the critical assumptions of the DiD model is that price trends of treatment and control groups are the same in the absence of treatment. We compare the trends before the discovery of PFAS in 2014 (pretreatment) and assume the trend would continue after 2014 if not for the treatment. We visually evaluate home price trends by plotting conditional average home prices in contaminated and non-contaminated locations. We test the null hypothesis that price trends in the treatment and control groups are similar in the absence of treatment using equation (2) (Anica and Elbakidze 2023; Beland and Oloomi 2019).

$$P_{igt} = \boldsymbol{\beta_1 H_{igt}} + \sum_{\tau=2010}^{2019} \beta_\tau \boldsymbol{\tau} * C_{it} + \boldsymbol{\psi_g} + \boldsymbol{\mu_{it}} \dots\dots\dots.(2)$$

where, the notations are the same as in equation 1. The difference is that treatment indicator, C, is included as an interaction with individual year fixed effects rather than the pre versus post treatment indicator. The parameter of interest, $\boldsymbol{\beta_\tau}$, is a vector of coefficients that show the differences in treatment and control groups relative to the price of the control homes in base year (2010). A statistically significant β_τ implies that there is a statistical difference in the prices of treatment and control homes in year τ relative to the control group in the base year 2010. On the other hand, statistically insignificant coefficients imply that that there is not a significantly

[6] Results from models that include transactions of homes with private wells are consistent with the results and are available upon request. We exclude those results from this draft because PFAS contamination status for private wells is difficult to establish. As a result, the models that include these data rely on strong assumptions that these properties belong to either the control or the treatment group.

different change in treatment and control group house prices in year τ relative to control group in the base year. Statistically insignificant β_τ for 2011-2013 suggest that price trends of treatment and control groups do not differ significantly.

We also use an even study specification to examine pre-treatment parallel trends. Following the Miller (2023) and Clarke & Tapia-Schythe (2021) we conduct event study using equation (3).

$$P_{igt} = \sum_{\tau=2010}^{2012} \beta_\tau \, (Lag\ \tau)_{gt} + \sum_{\tau=2014}^{2019} \delta_\tau \, (Lead\ \tau)_{gt} \ + \boldsymbol{\beta_1 H_{igt}} + \beta_2 N_{igt} + \psi_g + \tau_t + \mu_{it} \ldots.(3)$$

Lags and Leads are binary variables and indicate the number of years between the date of transaction and the contamination event. For example, indicator variable for all sales in the contaminated PWS in 2013 is lag 1 as it is one year before the detection of contamination in 2014. We normalize coefficient for the year before the contamination detection to 0 ($\beta_{2013} = 0$) by omitting the indicator for lag 1 which enables us to capture the baseline difference in house sale price between the areas where the contamination does and does not happen. Never contaminated houses act as counterfactuals on which the estimation of the contamination impact is based. Differences between contaminated and non-contaminated houses are anchored at omitted base period. Hence, lags and leads capture the difference in price trends between treated and control group, compared to the prevailing trend difference in the omitted base period. The non-significant β_τ demonstrate the absence of a difference in trends before the contamination which indicates consistency with the parallel trend assumption.

Spatial spillover

A fundamental assumption of DiD hedonic models is that the control group, serving as the comparison benchmark, is unaffected by the treatment. However, spillover effects, where the treatment's impact extends to the control group, are common in observational data (Abadie and Cattaneo 2018; Vazquez-Bare 2023). In DiD hedonic property value studies, where treatment and control groups are located next to each other, spillover effects can be present.

The common practice to deal with spillover effect is dropping the sample up to certain distance from the border of the treatment group based on educated guess. But the disadvantage of this approach is loss of degrees of freedom, sacrificing efficiency with no gain in bias if true spillover effect is absent. Therefore, in this paper we formally test the presence of spillover effects before deciding on dropping samples.

Two opposing spillover effects may be encountered. The first type of spillover effect is encountered when discovery of the contaminant reduces the prices of houses not only in the contaminated location but also near the contaminated location. Demand for properties that are adjacent to the contaminated PWS can be suppressed due to perceived potential exposure (Burton, Maas and Lee 2022; Hansen, Benson and Hagen 2006). This spillover effect can result in downward bias of the treatment effect estimate.

The second type of spillover effect is realized when the discovery of contaminant reduces the house price in contaminated location and increases prices of non-contaminated properties in the control group. This spillover effect can occur when homeowners avoid the contaminated location but prefer to live as close as possible to the affected neighborhood. For example, if the affected neighborhood is downtown, as is the case in our context with the affected PWS in downtown Harrisburg, then buyers may prefer properties that are as close as possible but outside of potential exposure to the health risk. As a result, prices of properties just outside of the contaminated PWS can increase due to the treatment. This spillover effect can result in an upward bias of the DiD treatment effect estimates.

To illustrate, suppose the average house prices before the discovery of contamination $(\Gamma = 0)$ in the non-contaminated (C = 0) and contaminated (C = 1) locations are $\bar{P}_{(\Gamma=0)(C=0)}$ and $\bar{P}_{(\Gamma=0)(C=1)}$, respectively. Similarly, average house prices after the discovery of contamination $(\Gamma = 1)$ in the non-contaminated and contaminated locations are $\bar{P}_{(\Gamma=1)(C=0)}$ and $\bar{P}_{(\Gamma=1)(C=1)}$, respectively. Then, the DiD estimator is obtained as

$$\hat{\beta}_4 = \left(\bar{P}_{(\Gamma=1)(C=1)} - \bar{P}_{(\Gamma=0)(C=1)}\right) - \left(\bar{P}_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \ldots . (4)$$

Assuming that home prices are generally higher in period 1 than 0,

$$\bar{P}_{(\Gamma=1)(C=1)} > \bar{P}_{(\Gamma=0)(C=1)} \Longrightarrow \left(\bar{P}_{(\Gamma=1)(C=1)} - \bar{P}_{(\Gamma=0)(C=1)}\right) > 0 \ldots .. (5) \text{ and}$$

$$\bar{P}_{(\Gamma=1)(C=0)} > \bar{P}_{(\Gamma=0)(C=0)} \Longrightarrow \left(\bar{P}_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) > 0 \ldots \ldots (6)$$

then, with a negative treatment effect such as contamination,

$$\left(\bar{P}_{(\Gamma=1)(C=1)} - \bar{P}_{(\Gamma=0)(C=1)}\right) \leq \left(\bar{P}_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \ldots . (7)$$

Hence, $\hat{\beta}$ is negative,

$$\hat{\beta} = -c \ \ldots . (8)$$

If the first kind of spillover effect occurs than average house price of the control group, let say $\bar{P}'_{(\Gamma=1)(C=0)}$, is less than the $\bar{P}_{(\Gamma=1)(C=0)}$, because the sample used to calculate $\bar{P}'_{(\Gamma=1)(C=0)}$ includes homes with lower prices than what would be the case without spillover. Since $\bar{P}_{(\Gamma=0)(C=0)}$ is same for both non-spillover and spillover scenarios

$$\left(\bar{P}'_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \leq \left(\bar{P}_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \ldots . (9)$$

The spillover effect does not affect the value of $\left(\bar{P}_{(\Gamma=1)(C=1)} - \bar{P}_{(\Gamma=0)(C=1)}\right)$ in equation (4). Therefore,

$$\hat{\beta}' = -c' \text{ and}$$

$$-c' > -c \text{ or}$$

$$c' < c \quad \ldots..(10)$$

Hence, downward bias is present in the case of the first spillover effect.

In the second type of spillover, the average house price in the non-contaminated location, $\bar{P}''_{(\Gamma=1)(C=0)}$, is higher than what would have been the case with no spillover $\bar{P}_{(\Gamma=1)(C=0)}$. Since $\bar{P}_{(\Gamma=0)(C=0)}$ is same for both non-spillover and spillover scenarios, $\bar{P}''_{(\Gamma=1)(C=0)} > \bar{P}_{(\Gamma=1)(C=0)}$ implies

$$\left(\bar{P}''_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \geq \left(\bar{P}_{(\Gamma=1)(C=0)} - \bar{P}_{(\Gamma=0)(C=0)}\right) \ldots.(11)$$

Since the spillover effect does not affect the value of $\left(\bar{P}_{(\Gamma=1)(C=1)} - \bar{P}_{(\Gamma=0)(C=1)}\right)$ in equation (4),

$$\hat{\beta}'' = -c'' \text{ and}$$

$$-c'' < -c$$

$$c'' > c$$

Hence, an upward bias is present in the case of the second spillover type.

We hypothesize that both types of spillover effects may be present. The negative spillover effect can affect properties that are adjacent to the contaminated PWS boundary because buyers avoid even the properties that are outside of the affected area but close enough to raise concerns. The positive effect may affect properties that are closest but not adjacent to the boundary as demand for those properties increases if buyers are interested in properties that are close to the affected PWS but far enough to be less of a concern for contamination.

To test for the spillover effects, we split the control group of homes in the non-contaminated areas of Dauphin County into mock treatment and control groups. Two treatment designs are considered. In the first design, the mock treatment group includes all transactions for homes located within one mile outside of the contaminated PWS. The control group includes all transactions outside of the one-mile buffer in the noncontaminated areas of Dauphin County. Similarly, in the second design, the treatment group includes all the transactions of homes located more than one but less than two miles away from the contaminated PWS. The control group includes all transactions of homes located more than two miles away from the contaminated PWS. The DiD model is used for each of the treatment designs to test for the presence of the spillover effect.

The presence of the first types of spillover bias (downward) is identified if DiD interaction coefficient is negative and significant, whereas second types of spillover bias (upward) is identified if the coefficient is positive DiD. In both cases, the spillover implies that the control group is not suitable for proper DiD analysis without adjustment. One option to adjust the control group in the presence of the spillover effect is to remove the transaction that are affected by the spillover from the control group.

Propensity Score matching and weighted DiD

The reliability of the DiD approach rests on the assumption that treatment and control groups are equivalent in all respects other than the treatment. This is a difficult condition to secure in pooled cross-sectional data. Treatment and control groups may differ in unobserved ways besides treatment, which can contaminate the analysis and result in biased estimates.

Propensity score matching (PSM) techniques are commonly used to account for unobserved differences (Anica and Elbakidze 2023). The propensity score is the probability of the individual belonging to the treatment group based on the covariates other than the outcome variable. The PSM technique identifies the control and treatment groups that match in terms of the probability of receiving treatment. We match pretreatment groups with pre control, and post treatment with post control groups using the propensity score weighted approach following the Stuart et al. (2014). The observations are divided into four groups, pre-treated (1), pre-control (2), post-treated (3), and post-control (4) to estimate the propensity scores as the probabilities of being in group 1 versus other groups. Using multinomial logistic regression, we obtain probabilities p_{ig} for each transaction i belonging to group g. In the matched DiD model, the weight of each observation i s:

$$w_{i(g)} = \frac{(p_{i1}|X)}{(p_{ig}|X)} \dots \dots (12)$$

were, $w_{i(g)}$is the weigh for transaction i, which represents the relative probability of transaction i belonging to group 1 (pre contamination treatment group) relative to the probability of belonging to the actual group the transaction is in (g). These weights are used in the DiD regression assuring that each group is weighted to be similar to group 1.

Data and Summary Statistics

EPA's UCMR3 program detected five types of PFAS, including PFHpA, PFHxS, PFNA, PFOS, and PFOA in one of the twenty-seven PWSs in Dauphin County, Pennsylvania in 2014. The affected PWS serves thirty thousand residential homes in downtown Harrisburg, the capital of PA. The surrounding metropolitan area extends into Dauphin and Cumberland counties with populations of approximately two hundred and ninety and two hundred and sixty thousand, respectively. Single family-owned residential house transaction data from 2010 to 2019 were collected from the Dauphin County's Property and Taxes Assessment and Tax Claim department website[7] and from the Cumberland County's Property Mapper website[8], respectively. We collect the arm length residential property transactions excluding mobile homes. Transactions between family members, transactions with sale price less than ten thousand or exceeding one million dollars are excluded. Sheriff sale[9] transactions are also dropped. Out of 5,431 transactions in contaminated PWS, 1,685 are from before the contamination discovery and 3,746 are after (Table 1). Approximately 24% and 18% of transactions in Dauphin and Cumberland Counties, respectively rely on private wells. Since the private wells were not tested for PFAS, we exclude all the transactions for homes that rely on private wells for their drinking water. With this exclusion, the total transactions for Dauphin and Cumberland Counties are 13,139 and 13,016 respectively. The dataset includes property identification number (PIN), address, construction year, sale date, lot size, living area, bedrooms, bathrooms, number of stories, presence of finished basement.

We geotagged each transaction by joining the parcel boundary shape file, obtained from the Dauphin County GIS Data Portal,[10] with the cleaned transaction data using property identification number (PIN). Municipality and school district shape files are obtained from Pennsylvania Spatial Data Access (PASDA) website[11]. PWS shape files is used to distinguish

[7] https://www.dauphincounty.gov/government/support-services/property-taxes
[8] https://www.cumberlandcountypa.gov/2295/Web-Mapping
[9] A sheriff's sale is a public auction of property that has been repossessed and is being sold by court order to satisfy debts that are in default.
[10] https://data-dauphinco.opendata.arcgis.com/
[11] https://www.pasda.psu.edu/

properties that rely on public water supply versus private wells (Figure 1). Dauphin county has 27 PWS, 11 School Districts and 40 municipalities. The contaminated PWS supplies water partially or completely to 11 municipalities and four school districts in Dauphin County (see Figure 1).

Table 1 presents summary statistics for the control and treatment groups. Thirty five percent of transactions in Dauphin County are in the treatment group. The rest of the transactions in Dauphin (n= 7,707) and Cumberland counties (n = 13,015) form various control groups. Approximately 70% of the transactions are in the post treatment period.

The average house price in the contaminated PWS is $153,000, which is $7,000 less than the rest of Dauphin County and $75,000 less than Cumberland County. The home prices in the contaminated PWS increased by $8,000 post contamination period relative to pre contamination, while corresponding prices in the rest of Dauphin and Cumberland counties increased by $15,000 and $13,000, respectively.

The concentrations of PFOA, PFOS, PFHpA, PFHxS, and PFNA in contaminated PWS were 38, 363, 24, 209, and 47 ppt, respectively. PFOS was detected above EPA 2009's provisional Health Advisory (HA) thresholds which was 200 ppt[12]. Although there was no official HA for PFHpA, PFHxS, and PFNA at the time of detection, their harmful effects on human health have been recognized (Turley et al. 2013; Li et al. 2021; Narizzano et al. 2023). As such, positive values for these chemicals can be alarming for homeowners who own or are interested in owning properties serviced by the contaminated PWS.

[12] https://www.epa.gov/sites/default/files/2015-09/documents/pfoa-pfos-provisional.pdf

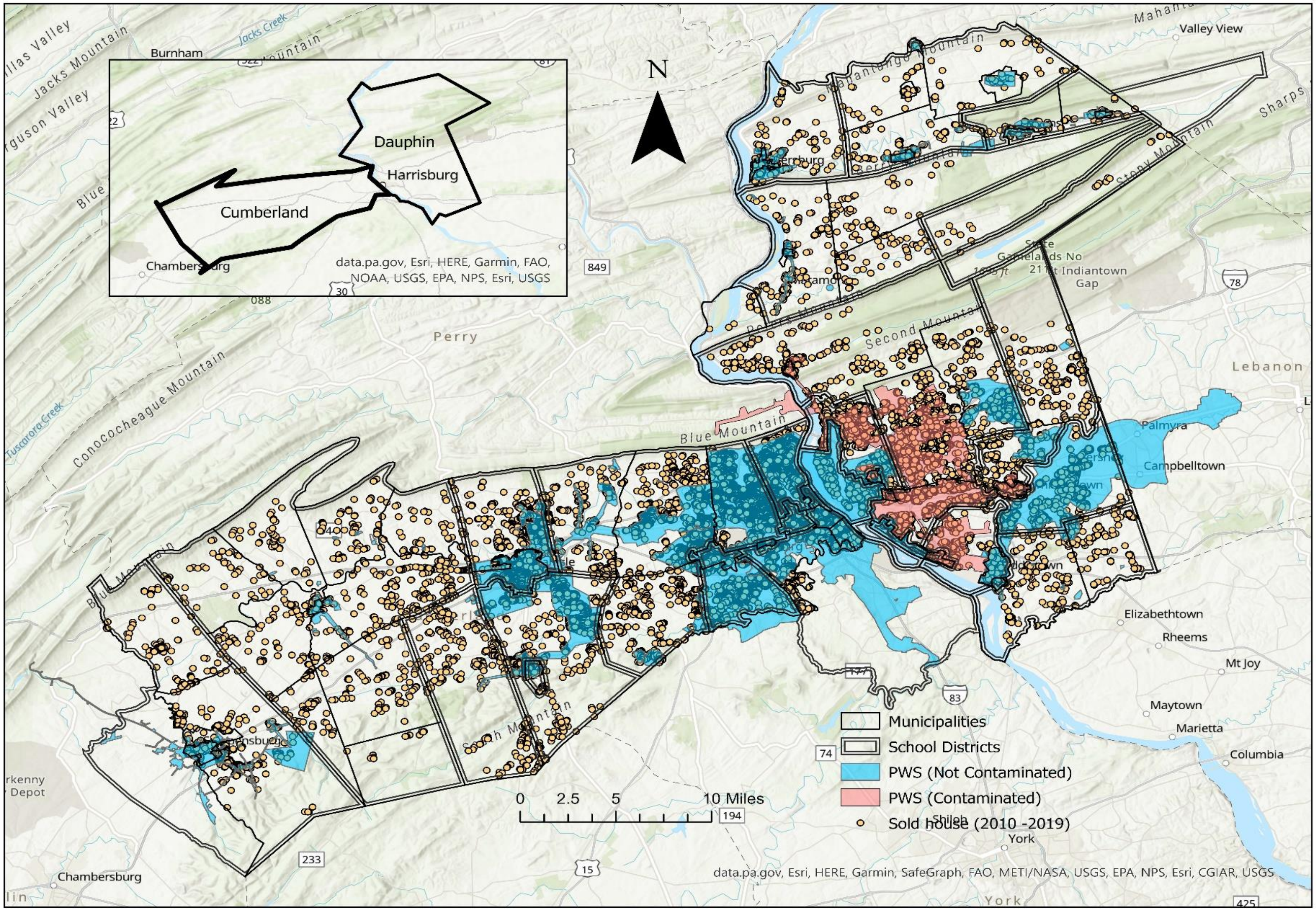

Figure 1: Residential property transactions, Public Water Service (PWS) boundaries, municipalities, and school districts in Dauphin and Cumberland County, Pennsylvania. Inset map depicts the relative location of Cumberland and Dauphin County.

Table 1: Summary statistics of the data used in the study.

	(1)			(2)			(3)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Panel A: Contaminated PWS in Dauphin									
	Before (n=1685)			After (n=3746)			Overall (n=5431)		
Sale Price (in thousand $)	148	11	795	156	13	900	153	11	900
Lot Size (Acres)	0.28	0.01	13	0.26	0.01	13	0.27	0.01	13
Total Living Area (sq. ft.)	1498	288	8078	1501	558	8078	1500	288	8078
Year Built	1963	1750	2013	1964	1800	2017	1964	1750	2017
Age at Sale (year)	49	0	260	53	0	219	51	0	260
Number of Rooms	2.99	1	7	2.97	1	6	2.98	1	7
Number of Full bathrooms	1.47	1	5	1.48	1	5	1.48	1	5
Number of Half Bathrooms	0.49	0	3	0.52	0	3	0.51	0	3
Number of Stories	1.44	1	3	1.47	1	3	1.46	1	3
Finished Basement (present =1, Absent=0)	0.35	0	1	0.35	0	1	0.35	0	1
Panel B: Not Contaminated Dauphin									
	Before (n=2,434)			After (5,273)			Total (n=7,707)		
Sale Price (in thousand $)	139	10	935	155	10	910	150	10	935
Lot Size (Acres)	0.19	0	8.2	0.19	0	7.59	0.19	0	8.2
Total Living Area (sq. ft.)	1710	459	5428	1685	432	7169	1693	432	7169
Year Built	1949	1800	2013	1947	1800	2019	1948	1800	2019
Age at Sale (year)	63	0	212	70	0	216	67	0	216
Number of Rooms	3.27	1	9	3.21	1	8	3.23	1	9
Number of Full bathrooms	1.50	1	6	1.47	1	7	1.48	1	7
Number of Half Bathrooms	0.45	0	3	0.44	0	3	0.44	0	3
Number of Stories	1.82	1	3	1.80	1	4	1.81	1	4
Finished Basement (present =1, Absent=0)	0.20	0	1	0.20	0	1	0.20	0	1
Panel C: Cumberland									
	Before (n=3,440)			After (n =9,575)			Total (n= 13,015)		
Sale Price (in thousand $)	220	10	999	233	12	998	230	10	999
Lot Size (Acres)	0.36	0	7.41	0.33	0	10.26	0.34	0	10.26
Total Living Area (sq. ft.)	1946	500	8790	1901	338	7215	1913	338	8790
Year Built	1975	1775	2013	1975	1773	2019	1975	1773	2019
Age at Sale (year)	37	0	238	42	0	243	41	0	243
Number of Rooms	3.24	1	7	3.22	1	9	3.23	1	9
Number of Full bathrooms	1.80	0	5	1.80	1	6	1.80	0	6
Number of Half Bathrooms	0.67	0	3	0.66	0	8	0.66	0	8
Number of Stories	1.66	1	3	1.68	1	3	1.67	1	3
Finished Basement (present =1, Absent=0)	0.30	0	1	0.31	0	1	0.31	0	1

Note: This table presents summary statistics for the dataset employed in the study. Column 1 delineates summary statistics pertaining to house sales before the discovery of contamination, while Column 2 summarizes statistics post-contamination discovery. Column 3 aggregates overall statistics encompassing both pre- and post-contamination discovery. Panel A shows transaction summary for the contaminated location in Dauphin County. Panel B displays transaction summaries for the noncontaminated part of Dauphin County. Similarly, Panel C presents transaction summaries for Cumberland County, where no contamination was detected, serving as one of the control groups in our analysis.

Results

Spillover effect

Table 2, panel A shows a negative and statistically significant spillover effect for the properties located within one mile of the contaminated PWS. Relative to the properties further away from the affected PWS, the prices of homes within one mile of contaminated PW boundary decrease by $10,500 to $14,500. This result suggests that buyers avoid properties that are located within a mile from the contaminated PWS.

Similarly, an upward spillover effect is observed within a one to two-mile radius. To diagnose this effect, we dropped the subsample of transactions within one mile from the contaminated PWS as these properties experience a decrease in prices due to contamination. Hence, we conduct DiD analysis where all transactions within one to two miles around the contaminated PWS comprise a pseudo treatment group while all transactions beyond the two-mile boundary form the control. The result shows an upward effect ranging from $7,600 to $10,700 (Table 2, Panel B). This result suggests that prices of properties in the one-to-two-mile buffer around the contaminated PWS increased after the discovery of PFAS. Buyers who normally prefer properties in or close to downtown Harrisburg bought homes in the one-to-two-mile zone as an acceptable balance of proximity to downtown and isolation from the contaminated PWS. In a similar manner, we examine the spillover effects in the 2:3, 3:4, …9:10 mile buffers and detect no similar statistically significant effects[13]. Therefore, for our main analyses, we remove the transactions of properties located within the 2-mile buffer around the boundary of the contaminated PWS.

Table 2: Diagnostic DiDs for the spillover effects.

	(1)	(2)	(3)	(4)
Panel A: 0-1 mile from contaminated PWS as treatment				

[13] The results of the 2:3-mile buffer are provided in table 2 panel C. The results for rest of the buffer analysis are available upon request.

	(1)	(2)	(3)	(4)
contamination*post	-14,536*** (3,307)	-10,517*** (3,074)	-10,878*** (2,987)	-10,508*** (2,988)
Observations	7,707	7,707	7,707	7,707
R-squared	0.619	0.673	0.693	0.692
Panel B: 1-2 mile from contaminated PWS as treatment				
contamination*post	10,728** (4,929)	7,648* (4,550)	9,205** (4,394)	9,738** (4,394)
Observations	4,641	4,641	4,641	4,641
R-squared	0.606	0.671	0.694	0.693
Panel C: 2-3 mile from contaminated PWS as treatment				
contamination*post	1,196 (5,747)	2,273 (5,187)	1,573 (5,024)	2,702 (5,023)
Observations	3,190	3,190	3,190	3,190
R-squared	0.555	0.640	0.665	0.663

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note. All the transactions in the contaminated PWS are dropped. In panel A, properties within one mile of the contaminated PWS comprise the treatment group, while properties beyond one mile are control. In panel B, all transactions within one mile from contaminated PWS are dropped and transactions between one to two miles from the contaminated PWS boundary comprise the treatment group. Properties two or more miles away from the boundary are considered control. Similarly, in panel C, all transactions within two miles of the contaminated PWS are dropped and transactions two to three miles away comprise the treatment group. Properties further than three are control. Model 1 includes year fixed effects, Model 2 adds PWS fixed effect, Model 3 adds municipality fixed effect and Model 4 uses School District FE instead of Municipalities FE. All models use lot size (acres), living area (sq ft), age, number of bedrooms, number of full bathrooms, number of half bathrooms, number of stories, and presence of finished basement in house as covariates.

Parallel Trend

Figure 2 shows price trends in treatment and control groups. Panels A, B, and C compare price trends in the treatment group with different control groups including all properties outside of the contaminated PWS, all properties outside of the contaminated PWS and the two-mile spillover buffer around its boundary, and Cumberland County as a control, respectively. Panels B and C show visually more satisfactory trends than panel A, which is consistent with our preferred model selection based on the spillover effect results. Before the discovery of the contamination, average home price trends are similar in the contaminated PWS and the rest of Dauphin County outside of the 2-mile buffer zone around the affected PWS. After 2014 the price gap widened. Similar story is apparent from comparing transactions in the contaminated PWS and Cumberland County (Figure 2 C). Panel D shows that the price trends are similar to the overall house price index (HPI) for all transactions in Pennsylvania from 2010 to 2019 (USFHFA 2023)

Figure 3 visually presents the results of the formal parallel trends assumption tests. The interaction terms for year fixed effects and the treatment group indicator are statistically insignificant in

2010 through 2014. Hence, the tests fail to reject the hypothesis that price trends of transactions in treatment and control groups before treatment are similar.

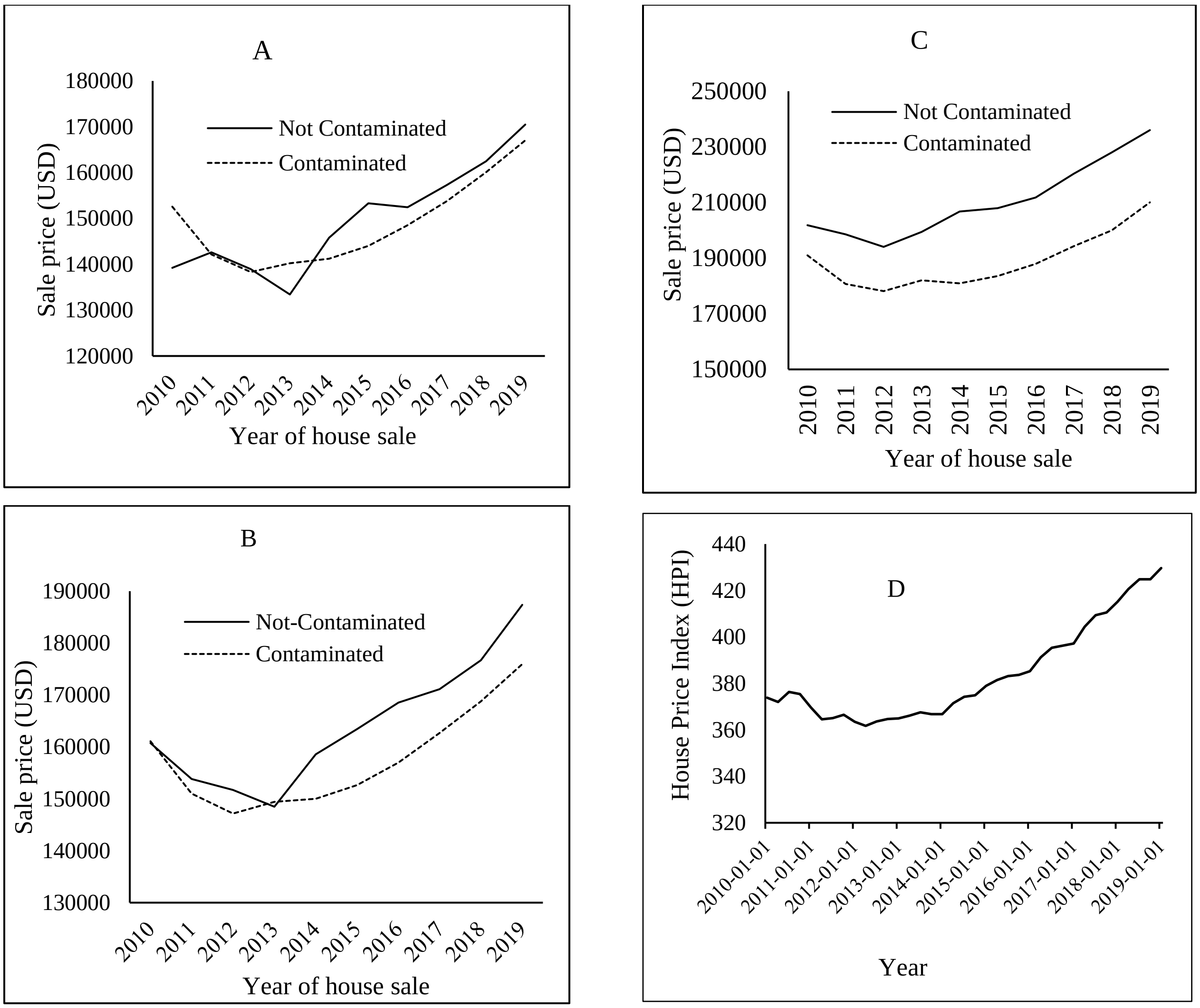

Fig 2: Prices trends in treatment and control groups.
Note: panel A and B show home price trend in contaminated PWS and rest of Dauphin County without and with the two miles buffer, respectively. Panel C uses the transactions in Cumberland as the treatment group. Panel D shows overall house price index (HPI) trend for Pennsylvania from 2010-2019. HPI trend data was retrieved from the FRED website.

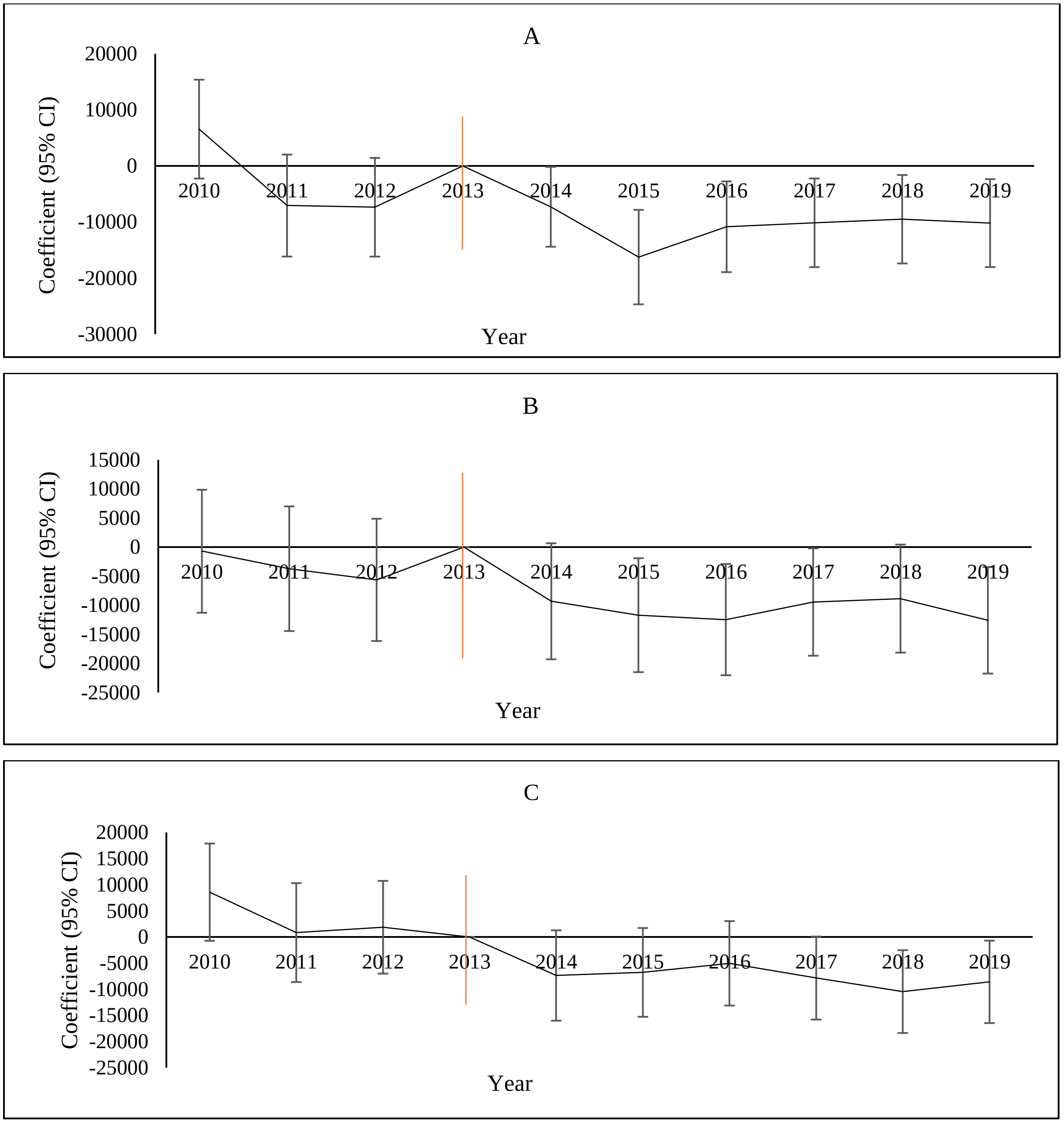

Figure 3: Parallel trend test results. Panel A, B and C show the pre and post 2013 house price difference between treatment and control groups including the contaminated PWS, non-contaminated Dauphin, noncontaminated dauphin with the two-mile buffer, and Cumberland County, respectively, relative to the baseline control group in 2013.

DiD Results

We focus on discussing the results from the DiD model with a two-mile buffer around the treatment group. Transactions in the buffer zone are excluded from the main regression models due to the spatial treatment spillover effects. However, we also obtain results from the models without buffer exclusion, which generally are consistent with the preferred specification. These results are provided in appendix Table A1.

The estimated treatment interaction effect coefficients from various DiD models with the two-mile buffers are presented in Table 3. The corresponding full results that include all control variables are provided in appendix Tables 2a-2g. Models 1-4 differ in terms of fixed effects. Starting with model 1, all models include year fixed effects. PWS fixed effects are added in models 2 through 4. Model 3 adds municipality fixed effects, whereas model 4 uses school district instead of the municipality FE. Municipality and school district fixed effect cannot be included in the same model as each school district includes one or more municipalities, which results in perfect multicollinearity. Since the PWS boundary never coincide with school district and municipality boundary, PWS fixed effect can be used in conjunction with municipality or school district fixed effects. School district fixed effect controls for time-invariant unobservable neighborhood characteristics that influence house prices, as people often purchase homes based on school districts characteristics (Ding et al. 2023; Ferreyra 2007; Figlio and Lucas 2004). On the other hand, municipality fixed effects control for the heterogeneity at the municipal level.

Panels A through F report results from regressions with various control group specifications that differ in terms of the distance from the contaminated PWS. For example, in panel A, the treatment group includes transactions inside the contaminated PWS, while control group includes homes located further than 2 but within 3 miles from the boundary of the affected PWS. Similarly, panels B, C, D, E and F use the same treatment group, but the control groups include properties in the 2:4, 2:5, 2:6, 2:7, and 2:12 mile rings around the contaminated PWS, respectively. The parallel trend graphs for house prices based on the various distance ring are presented in Appendix Figure F1. Finally, panel G shows the results from the model with the whole Dauphin County except for the contaminated PWS and two-mile buffer transactions as a control group. All models use transactions of homes that rely only on the public drinking water supply and exclude homes with private drinking water wells[14].

The results in table 3 show that the properties in the contaminated PWS lost between $8,000 and $13,600 depending on fixed effects and the control group specifications. Estimated decline in property values in the contaminated PWS varies depending on the control group as a benchmark. However, properties in the nearest ring are likely to be better benchmarks. Therefore, the estimates in panels A and B, which range between $9,000 and $13,000 are probably the most reliable.

[14] PFAS contamination status of private wells can not be established. Therefore, it is difficult to confidently assign these transactions to either the control or the treatment groups. Nevertheless, we have the results from the models that include private well data, which are generally consistent with our main findings. These results are available upon request.

Table 3: Effect of PFAS contamination on house sale prices in Dauphin County, PA. Estimation from two-mile buffer approach.

	(1)	(2)	(3)	(4)
Panel A: one mile from two-mile buffer				
contamination*post	-9,243*** (2,787)	-9,663*** (2,761)	-8,809*** (2,597)	-9,433*** (2,622)
Observations	6,913	6,913	6,913	6,913
R-squared	0.621	0.628	0.672	0.665
Panel B: two miles from two-mile buffer				
contamination*post	-12,157*** (2,868)	-12,967*** (2,831)	-11,505*** (2,643)	-11,513*** (2,664)
Observations	7,574	7,574	7,574	7,574
R-squared	0.603	0.614	0.664	0.658
Panel C: three miles from two-mile buffer				
contamination*post	-12,046*** (2,820)	-13,169*** (2,784)	-12,117*** (2,624)	-11,721*** (2,642)
Observations	7,674	7,674	7,674	7,674
R-squared	0.604	0.615	0.660	0.654
Panel D: four miles from two-mile buffer				
contamination*post	-12,753*** (2,797)	-13,607*** (2,761)	-12,750*** (2,608)	-12,372*** (2,626)
Observations	7,718	7,718	7,718	7,718
R-squared	0.603	0.614	0.658	0.652
Panel E: five miles from the two -mile buffer				
contamination*post	-11,950*** (2,748)	-12,641*** (2,714)	-11,805*** (2,588)	-11,472*** (2,604)
Observations	7,825	7,825	7,825	7,825
R-squared	0.601	0.611	0.648	0.643
Panel F: 10 miles from two-mile buffer				
contamination*post	-11,882*** (2,733)	-12,371*** (2,688)	-11,505*** (2,562)	-11,221*** (2,578)
Observations	7,879	7,879	7,879	7,879
R-squared	0.598	0.612	0.649	0.643
Panel G: contamination vs rest of Dauphin (except two miles buffer)				
contamination*post	-10,515*** (2,644)	-8,755*** (2,429)	-8,292*** (2,320)	-7,930*** (2,333)
Observations	8,622	8,622	8,622	8,622
R-squared	0.551	0.623	0.658	0.653
Year FE	Yes	Yes	Yes	Yes
PWS FE	-	Yes	Yes	Yes
Municipality FE	-	-	Yes	-
School District FE	-	-	-	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note. The distance of each house in Dauphin County, PA from the boundary of the contaminated PWS has been identified and any house sale from two miles from the contaminated PWS border has been dropped. This two-mile distance is called buffer, excluding any house that has spillover effect. Panel A compares the house sale price between houses in the contaminated PWS and all houses within 1 mile outer from the two-mile buffer. Similarly, panel B, panel C, panel D, panel E, and panel F, compares houses sales prices in 2, 3, 4, 5, and10 miles from the boundary of two-mile buffer with houses sales within contaminated PWS. Panel G compares house sale prices in contaminated PWS with all house sales outside the two-mile buffer and inside the Dauphin County boundary. Full set of results is provided in Appendix Table A2.1 -A2.7.

Robustness Tests

We explore the robustness of the DiD result using three approaches. First, the effect of the contamination was estimated based on the treatment group from the Contaminated PWS of Dauphin County and control group from Cumberland County. Parallel trends in Figure 2,C and parallel trend results in Figure 3,C show that price trends in these treatment and control groups before 2014 are comparable. Therefore, a significant DiD interaction coefficient in this regression will corroborate the main result in Table 3. The second approach involves propensity score matching and weighted DiD and third approach involves the placebo test.

Table 4 shows the effect of contamination on prices in Harrisburg relative to prices in Cumberland County. The results are statistically significant and vary from $10,500 to $11,000, depending on the fixed effect specification. The magnitude of the estimated decline in property values supports our main results in Table 3.

Table 4: DiD results with transactions in Cumberland County as control.

	(1)	(2)	(3)	(4)
Contamination*Post	-10,480***	-11,124***	-10,614***	-10,980***
	(2,097)	(2,062)	(2,015)	(2,022)
Observations	18,446	18,446	18,446	18,446
R-squared	0.740	0.749	0.762	0.759
Year FE	Yes	Yes	Yes	Yes
PWS FE	-	Yes	Yes	Yes
Municipality FE	-	-	Yes	-
School District FE	-	-	-	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note. The models exclude properties that depend on private wells. Models 1 through 4 and covariates are the same as table 3. Full set of results is provided in Appendix Table A3

Table 5 presents the result from propensity score weighted DiD models. The control group in this regression includes Dauphin County properties that rely on public drinking water systems outside of the contaminated PWS and the two-mile buffer zone around it. The propensity score results show a $10,800 decline in house price in contaminated PWS after the discovery of the PFAS. These results are consistent with Table 3, supporting our main findings.

Table 5: Propensity score matching weighted DiD regressions.

	Propensity Score with Weighted-DiD
Treatment*post	-10,815*** (1,871)
Observations	8,622
R-squared	0.679
Year FE	Yes
PWS FE	Yes
School District FE	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note: The covariates used here are the same as Table 3.

The Placebo test involves constructing an artificial treatment group composed of randomly selected properties and comparing it with the true control groups (Beland and Oloomi 2019; Eggers, Tuñón and Dafoe 2023). A non-significant result in such a comparison provides additional support for the DiD results in Table 3 (Athey and Imbens 2017). We conduct three placebo tests by forming three sets of artificial treatment groups and comparing them with our true control group. The control group for all placebo tests remains the same and is composed of all PWS dependent properties in Dauphin County except for the transactions in the contaminated PWS and in the 2-mile buffer zone.

In the first placebo test (Table 6, Panel A), the treatment group comprises transactions for all homes with private drinking water wells in Dauphin County located outside of the contaminated PWS and the 2-mile buffer around it. For the second and third placebo tests (Table 6, Panels B and C), the treatment groups include homes with private wells and homes that rely on PWS for drinking water in Cumberland County, respectively. The parallel trend test results for the artificial treatment and control groups are presented in Appendix Figure F2. Three specifications – year FE, municipality FE, and school district FE – are used to ensure the consistency of the results. We observed no significant DiD coefficients consistently in the three presented models.

Table 6: Placebo test by considering non contaminated PWS served house transactions in Dauphin County as Control and here different transaction groups as treatment.

	(1)	(2)	(3)
Panel A: Homes with private wells in Dauphin as treatment			
Treatment*Post	225.5 (4,877)	2,497 (4,312)	2,562 (4,319)
Observations	4,604	4,604	4,604
R-squared	0.556	0.658	0.653
Panel B: Homes with private wells in Cumberland as Treatment			
Treatment*Post	3,111 (4,307)	5,012 (3,983)	5,255 (3,977)
Observations	6,125	6,125	6,125
R-squared	0.572	0.644	0.639
Panel B: PWS dependent homes in Cumberland as Treatment			
Treatment*Post	-522.1 (2,931)	2,193 (2,783)	2,990 (2,794)
Observations	16,191	16,191	16,191
R-squared	0.713	0.745	0.741
Year FE	Yes	Yes	Yes
Municipality FE	-	Yes	-
School District FE	-	-	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Note. All transactions within contaminated PWS and the 2-mile buffer around the contaminated PWS are dropped. The control group is formed using transactions in the non-contaminated PWSs of Dauphin County. Three artificial treatment groups are used with results in panels A, B, and C. All the models use lot size, living area of house (sq ft), age of house at sale, number of bedrooms, number of full bathrooms, number of half bathrooms, number of stories, and presence of finished basement in house as covariates.

Heterogeneity Analysis

In addition to the spatial heterogeneity explored in Panels A through F in Table 3, we also investigate the heterogeneity of the drinking water contamination impact across homes of various sizes and ages. Following Jenks (1967), we form five age brackets: 0-24, 25-49, 50-74, 75-99, and ≥ 100 years. Similarly, we form four size categories: 288-1426 sq. ft., 1427-2044 sq. ft., 2045-3044 sq. ft., and 3047-8078 sq. ft.

Triple DiD approach in equation 13 is used to explore the effect across different age and size categories houses.

$$P_{igt} = \beta_1 \boldsymbol{H}_{igt} + \beta_3 C + \beta_j \left(\Gamma * C * S_j\right) + \beta_k \left(\Gamma * C * A_k\right) + \psi_g + \tau_t + \mu_{it} \dots\dots(13)$$

Where, S_j are the age group indicators equal to 1 for all transactions in age group j, and 0 otherwise. Similarly, A_k are size group indicators equal to 1 for observations in size group k, and 0 otherwise. There are five age and four size groups with corresponding four and three triple DiD interaction coefficients. The base categories are 100 and more years old houses and 288-1426 sq. ft size houses.

The heterogeneity analysis results in Table 7 demonstrate the disparate price consequences of contamination across dwellings of varying ages and sizes. Notably, the degree of the impact is more pronounced for newer properties. For example, properties that are less than 75 year old depreciate by $19,000 to $35,000 more than their oldest counterparts. This disparity in impact is moderate for houses aged 0 to 24 years and 75 to 99 years ($22,000 to $33,000), and is most severe in houses aged 50 to 74 years ($37,000 to $40,000).

Some heterogeneity of the impact is also observed across size categories. Specifically, the largest properties depreciate by $64,000 to $76,000 more than the smallest properties. However, there is no statistically significant variation in the impacts across other size categories.

Table 7: Heterogeneous effect of contamination on different size and age group houses in Dauphin and Cumberland Counties, PA.

	(1)	(2)	(3)	(4)
After*Treatment*Age group 1	-22,578*** (8,373)	-21,333*** (7,709)	-29,580*** (7,432)	-29,681*** (7,483)
After*Treatment* Age group 2	-11,456 (8,853)	-8,232 (8,158)	-6,602 (7,860)	-6,283 (7,911)
After*Treatment* Age group 3	-34,817*** (8,577)	-32,574*** (7,908)	-33,222*** (7,620)	-33,518*** (7,667)
After*Treatment* Age group 4	-23,766** (11,232)	-19,369* (10,342)	-19,434* (9,966)	-19,618* (10,028)
After*Treatment* Size group 2	-2,441 (5,907)	-447.7 (5,442)	4,056 (5,248)	2,373 (5,280)
After*Treatment* Size group 3	-3,436 (7,785)	-8,689 (7,170)	-2,099 (6,914)	-3,634 (6,959)
After*Treatment* Size group 4	-64,138*** (17,289)	-75,949*** (15,919)	-70,120*** (15,342)	-73,153*** (15,436)
Observations	8,621	8,621	8,621	8,621
R-squared	0.588	0.651	0.678	0.673
Year FE	Yes	Yes	Yes	Yes
PWS FE	-	Yes	Yes	Yes
Municipality FE	-	-	Yes	-
School District FE	-	-	-	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: Transactions are categorized into five groups based on the age of the house at the time of sale and four groups based on the size of the house. Age groups 1 through 5 correspond to houses aged 0-24 years, 25-49 years, 50-74 years, 75-99 years, and 100 years and older, respectively. Size Groups 1 to 4 represent house sizes of 288-1426 sq. ft., 1427-2044 sq. ft., 2045-3044 sq. ft., and 3047-8078 sq. ft., respectively. Four columns represented four models with different fixed effects as described in table 3. The outputs in each of the four columns stem from separate triple DiD models. House structure characteristics, including lot size, number of bedrooms, number of full bathrooms, number of half bathrooms, and number of stories, are incorporated as covariates in all models.

Discussion and Conclusion

There are several noteworthy aspects of this study that warrant attention. First, we comprehensively examine the impact of PWS contamination, as a low-profile contaminant events, on the real estate market. PFAS, at the time of contamination, was not widely recognized as a drinking water contaminant compared to its present-day status. The estimated impact ranges from \$9,000 to \$13,000, amounting to a 6% to 8% reduction in house prices. This depreciation remains consistent across various control groups and spatial fixed effect specifications. The total loss in the residential housing stock in the contaminated area of Harrisburg is estimated to be between \$251 to \$363 million, based on the total number of single-family-owned residential housing units. However, it is important to note that our analysis provides a lower bound estimate of the external costs of PFAS contamination, as it solely focuses on house prices and excludes other impacts such as increased healthcare expenditures or compromised health and well-being. While these losses are significant, they are lower than some of the other PWS contamination events like Flint, Michigan, where lead contamination event in 2014 amounted to $29,000 average loss per property and $520-$559 million loss cumulatively (Christensen et al. 2023). The chemical spill in WV in 2014 caused a reduction in house prices ranging from $10,000 to $22,600 (Burton et al. 2022).

Second, this study highlights the enduring nature of the damage caused by PFAS contamination. Despite contamination being detected in Harrisburg in 2014, our event study demonstrates that house prices in the contaminated area continue to trend lower compared to non-contaminated locations even after five years of detection (2019). Similar trends have been observed by Christensen et al. (2023), who noted that house prices in Flint, Michigan, had not recovered even after years, despite authorities declaring the water safe to drink following extensive monitoring and reclamation efforts. Unlike in Flint, where Christensen et al. (2023) attributed the lack of recovery to public mistrust, the causes in our case may differ. Firstly, PFAS compounds exhibit persistence, resisting natural degradation and enduring indefinitely once introduced into a site (Cousins et al. 2020; Sáez, de Voogt and Parsons 2008). Secondly, even trace amounts consumed by individuals accumulate in the body, potentially reaching toxic levels over time (George, Baker and Baker 2023). Thirdly, PFAS compounds are not regulated under the Safe Drinking Water Act (SDWA), leading to inadequate monitoring in public water systems.

Third, we conceptualized and assessed two spillover effects using a robust DiD methodology. In our setting positive and negative spillover effects are present. These effects require appropriate control group specification to avoid bias in the estimate of the treatment effect.

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APPENDICES

Appendix A1: Effect of PFAS contamination on house prices in Dauphin County, PA.

	(1)	(2)	(3)	(4)
Panel G: Contaminated Vs rest of the county				
Treatment*post (Contaminated Vs Non-contaminated)	-10,543*** (2,194)	-9,024*** (2,014)	-9,284*** (1,952)	-9,177*** (1,959)
Observations	13,138	13,138	13,138	13,138
R-squared	0.590	0.656	0.678	0.675
Panel A: no buff one mile				
Treatment*post (1 mile)	-172.4 (2,007)	-1,546 (1,902)	-1,615 (1,817)	-1,775 (1,830)
Observations	8,497	8,497	8,497	8,497
R-squared	0.640	0.678	0.707	0.702
Panel B: no buff two miles				
Treatment*post (2 mile)	-7,818*** (2,069)	-7,137*** (1,939)	-7,328*** (1,878)	-7,404*** (1,885)
Observations	9,948	9,948	9,948	9,948
R-squared	0.646	0.691	0.711	0.708
Panel C: no buff three miles				
Treatment*post (3 mile)	-10,304*** (2,111)	-9,126*** (1,977)	-9,497*** (1,915)	-9,655*** (1,923)
Observations	11,429	11,429	11,429	11,429
R-squared	0.620	0.668	0.689	0.686
Panel D: no buff four miles				
Treatment*post (4 mile)	-11,895*** (2,266)	-10,530*** (2,103)	-10,812*** (2,025)	-10,843*** (2,034)
Observations	12,090	12,090	12,090	12,090
R-squared	0.600	0.657	0.683	0.679
Panel E: no buff five miles				
Treatment*post (5 mile)	-11,830*** (2,258)	-10,595*** (2,095)	-10,884*** (2,023)	-10,806*** (2,031)
Observations	12,190	12,190	12,190	12,190
R-squared	0.602	0.658	0.682	0.679
Panel F: no buff ten miles				
Treatment*post (10 mile)	-11,762*** (2,233)	-10,352*** (2,075)	-10,555*** (2,010)	-10,503*** (2,017)
Observations	12,395	12,395	12,395	12,395
R-squared	0.600	0.656	0.678	0.675
Year FE	Yes	Yes	Yes	Yes
PWS FE	-	Yes	Yes	Yes
Municipality FE	-	-	Yes	-
School District FE	-	-	-	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note. The distance of each house in Dauphin County, PA from the boundary of the contaminated PWS has been identified. Panel A compares the house sale price between houses in the contaminated PWS and all houses within 1 mile from the contaminated PWS. Similarly, panel B, panel C, panel D, panel E, and panel F, compares houses sales prices in 2, 3, 4, 5, and10 miles from the boundary of contaminated PWS with houses sales within contaminated PWS. Panel G compares house sale prices in contaminated PWS with all house sales outside the contaminated PWS and inside the Dauphin County boundary. Model 1 includes source of water fixed effect, Model 2 uses municipality fixed effect, Model 3 uses school district fixed effect and Model 4 uses the water source, municipality, and school district fixed effect. All models use year FE. All the models use lot size, living area of house (sq ft), age of house at sale, number of bedrooms, number of full bathrooms, number of half bathrooms, number of stories, and presence of finished basement in house as covariates.

Appendix A2.1: Full model results for Table 3, Panel A.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	21,528***	20,782***	21,674***	22,438***
	(1,483)	(1,475)	(1,398)	(1,405)
Living area (sq. ft.)	69.64***	67.88***	65.54***	65.96***
	(1.305)	(1.302)	(1.232)	(1.243)
House age (years)	-467.1***	-398.6***	-494.8***	-501.9***
	(20.07)	(20.74)	(21.68)	(20.96)
Number of bedrooms	9,079***	9,345***	8,210***	8,816***
	(796.2)	(789.0)	(750.8)	(755.0)
Number of full bathrooms	5,741***	5,657***	5,932***	5,763***
	(1,138)	(1,127)	(1,071)	(1,081)
Number of half bathrooms	8,103***	7,883***	6,702***	6,929***
	(1,131)	(1,120)	(1,058)	(1,067)
2.r_stories	-16,472***	-15,852***	-17,314***	-16,248***
	(2,280)	(2,259)	(2,142)	(2,160)
3.r_stories	-21,423***	-19,082***	-12,810***	-14,854***
	(1,380)	(1,381)	(1,345)	(1,328)
4.r_stories	-45,304***	-37,588***	-32,455***	-33,961***
	(6,097)	(6,075)	(5,735)	(5,784)
5.r_stories	-69,861***	-49,685***	-38,491***	-41,589***
	(2,855)	(3,325)	(3,164)	(3,177)
Finished basement	14,626***	14,538***	11,807***	11,928***
	(1,253)	(1,241)	(1,176)	(1,187)
Contaminated Vs Non-Contaminated	-9,243***	-9,663***	-8,809***	-9,433***
	(2,787)	(2,761)	(2,597)	(2,622)
Constant	62,589***	31,271***	32,408	41,138***
	(3,834)	(3,160)	(39,976)	(3,067)
Observations	6,913	6,913	6,913	6,913
R-squared	0.621	0.628	0.672	0.665
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.2: Full model results for Table 3, Panel B.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	16,007***	15,207***	18,131***	18,925***
	(1,668)	(1,653)	(1,557)	(1,563)
Living area (sq. ft.)	76.93***	74.45***	70.12***	70.65***
	(1.448)	(1.438)	(1.354)	(1.364)
House age (years)	-332.3***	-245.8***	-416.1***	-424.8***
	(22.55)	(23.11)	(24.13)	(23.39)
Number of bedrooms	10,280***	10,762***	9,034***	9,706***
	(913.5)	(902.1)	(852.2)	(854.8)
Number of full bathrooms	9,541***	9,054***	9,098***	8,809***
	(1,273)	(1,257)	(1,185)	(1,194)
Number of half bathrooms	11,368***	10,714***	9,149***	9,395***
	(1,279)	(1,263)	(1,183)	(1,191)
2.r_stories	-8,969***	-8,534***	-11,010***	-9,703***
	(2,583)	(2,548)	(2,400)	(2,415)
3.r_stories	-24,151***	-21,248***	-14,925***	-16,715***
	(1,573)	(1,566)	(1,506)	(1,488)
4.r_stories	-28,848***	-19,196***	-14,483**	-16,113**
	(6,956)	(6,897)	(6,459)	(6,503)
5.r_stories	-87,799***	-59,489***	-43,895***	-47,544***
	(3,195)	(3,751)	(3,546)	(3,553)
6.r_stories	-8,861	-20,928	-39,938	-40,431
	(51,109)	(50,432)	(47,054)	(47,451)
Finished basement	16,652***	16,561***	12,579***	12,639***
	(1,426)	(1,407)	(1,325)	(1,336)
Contaminated Vs Non-Contaminated	-12,157***	-12,967***	-11,505***	-11,513***
	(2,868)	(2,831)	(2,643)	(2,664)
Constant	41,588***	5,657	17,490	23,974***
	(4,208)	(3,572)	(47,098)	(3,461)
Observations	7,574	7,574	7,574	7,574
R-squared	0.603	0.614	0.664	0.658
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.3: Full model results for Table 3, Panel C.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	15,841***	15,209***	17,868***	18,940***
	(1,663)	(1,648)	(1,568)	(1,572)
Living area (sq. ft.)	77.91***	75.66***	72.06***	72.43***
	(1.437)	(1.427)	(1.353)	(1.363)
House age (years)	-320.9***	-235.4***	-378.6***	-387.3***
	(22.41)	(22.98)	(24.06)	(23.32)
Number of bedrooms	9,914***	10,298***	8,492***	9,166***
	(904.7)	(893.0)	(850.9)	(853.4)
Number of full bathrooms	9,983***	9,339***	9,505***	9,228***
	(1,268)	(1,252)	(1,190)	(1,199)
Number of half bathrooms	11,101***	10,442***	9,012***	9,279***
	(1,276)	(1,260)	(1,190)	(1,198)
2.r_stories	-9,330***	-8,872***	-11,183***	-9,770***
	(2,574)	(2,539)	(2,412)	(2,426)
3.r_stories	-24,605***	-21,913***	-16,482***	-18,249***
	(1,566)	(1,558)	(1,509)	(1,491)
4.r_stories	-28,943***	-19,486***	-15,081**	-16,741**
	(6,961)	(6,901)	(6,518)	(6,561)
5.r_stories	-87,751***	-60,024***	-45,627***	-49,241***
	(3,187)	(3,750)	(3,573)	(3,580)
6.r_stories	-8,710	-20,509	-36,746	-37,131
	(51,158)	(50,473)	(47,490)	(47,882)
Finished basement	17,297***	17,226***	13,931***	14,011***
	(1,421)	(1,402)	(1,330)	(1,340)
Contaminated Vs Non-Contaminated	-12,046***	-13,169***	-12,117***	-11,721***
	(2,820)	(2,784)	(2,624)	(2,642)
Constant	39,450***	4,412	15,332	20,415***
	(4,160)	(3,559)	(47,534)	(3,471)
Observations	7,674	7,674	7,674	7,674
R-squared	0.604	0.615	0.660	0.654
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.4: Full model results for Table 3, Panel D.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	15,566***	15,292***	17,824***	18,895***
	(1,657)	(1,645)	(1,569)	(1,572)
Living area (sq. ft.)	78.06***	75.68***	72.32***	72.70***
	(1.433)	(1.422)	(1.351)	(1.361)
House age (years)	-319.2***	-235.8***	-377.9***	-386.5***
	(22.36)	(22.90)	(24.03)	(23.29)
Number of bedrooms	9,895***	10,317***	8,544***	9,211***
	(902.4)	(890.7)	(850.5)	(852.9)
Number of full bathrooms	10,066***	9,387***	9,672***	9,393***
	(1,265)	(1,249)	(1,190)	(1,198)
Number of half bathrooms	11,180***	10,582***	9,146***	9,409***
	(1,273)	(1,256)	(1,189)	(1,197)
2.r_stories	-9,448***	-9,226***	-11,948***	-10,566***
	(2,547)	(2,512)	(2,393)	(2,406)
3.r_stories	-24,569***	-21,884***	-16,610***	-18,360***
	(1,562)	(1,552)	(1,507)	(1,489)
4.r_stories	-28,833***	-19,467***	-15,197**	-16,848**
	(6,960)	(6,898)	(6,529)	(6,571)
5.r_stories	-87,389***	-59,966***	-45,893***	-49,493***
	(3,182)	(3,747)	(3,577)	(3,584)
6.r_stories	-8,644	-20,315	-35,520	-35,912
	(51,155)	(50,457)	(47,576)	(47,966)
Finished basement	17,376***	17,244***	14,036***	14,118***
	(1,417)	(1,397)	(1,329)	(1,338)
Contaminated Vs Non-Contaminated	-12,753***	-13,607***	-12,750***	-12,372***
	(2,797)	(2,761)	(2,608)	(2,626)
Constant	37,909***	-35,758	14,907	19,717***
	(4,131)	(50,410)	(47,621)	(3,471)
Observations	7,718	7,718	7,718	7,718
R-squared	0.603	0.614	0.658	0.652
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.5: Full model results for Table 3, Panel E.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	15,930***	15,761***	18,136***	19,187***
	(1,651)	(1,641)	(1,580)	(1,582)
Living area (sq. ft.)	78.27***	76.06***	73.36***	73.70***
	(1.423)	(1.413)	(1.354)	(1.363)
House age (years)	-311.5***	-231.1***	-350.2***	-360.4***
	(22.21)	(22.79)	(24.07)	(23.32)
Number of bedrooms	10,106***	10,533***	9,200***	9,816***
	(894.2)	(883.3)	(850.7)	(852.9)
Number of full bathrooms	9,996***	9,323***	9,770***	9,483***
	(1,255)	(1,241)	(1,193)	(1,201)
Number of half bathrooms	11,210***	10,638***	9,238***	9,492***
	(1,261)	(1,245)	(1,190)	(1,197)
2.r_stories	-9,648***	-9,465***	-11,949***	-10,625***
	(2,530)	(2,497)	(2,401)	(2,413)
3.r_stories	-24,592***	-22,205***	-17,702***	-19,377***
	(1,545)	(1,537)	(1,504)	(1,486)
4.r_stories	-28,492***	-19,612***	-16,052**	-17,641***
	(6,944)	(6,888)	(6,580)	(6,619)
5.r_stories	-86,339***	-60,152***	-47,801***	-51,235***
	(3,165)	(3,735)	(3,597)	(3,603)
6.r_stories	-6,969	-18,128	-30,284	-30,629
	(51,052)	(50,395)	(47,970)	(48,332)
Finished basement	17,827***	17,733***	15,206***	15,281***
	(1,409)	(1,391)	(1,334)	(1,343)
Contaminated Vs Non-Contaminated	-11,950***	-12,641***	-11,805***	-11,472***
	(2,748)	(2,714)	(2,588)	(2,604)
Constant	35,051***	-36,741	10,259	14,457***
	(4,043)	(50,349)	(48,015)	(3,458)
Observations	7,825	7,825	7,825	7,825
R-squared	0.601	0.611	0.648	0.643
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.6: Full model results for Table 3, Panel F.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	15,765***	16,162***	18,332***	19,492***
	(1,649)	(1,631)	(1,572)	(1,572)
Living area (sq. ft.)	78.14***	75.77***	73.15***	73.45***
	(1.423)	(1.407)	(1.348)	(1.356)
House age (years)	-333.5***	-238.8***	-352.1***	-365.4***
	(21.93)	(22.42)	(23.80)	(22.91)
Number of bedrooms	10,302***	10,547***	9,131***	9,785***
	(892.5)	(878.1)	(846.4)	(847.9)
Number of full bathrooms	10,166***	9,255***	9,811***	9,478***
	(1,254)	(1,234)	(1,187)	(1,194)
Number of half bathrooms	10,963***	10,626***	9,323***	9,522***
	(1,258)	(1,237)	(1,183)	(1,189)
2.r_stories	-9,966***	-9,483***	-12,046***	-10,651***
	(2,524)	(2,481)	(2,386)	(2,397)
3.r_stories	-24,808***	-22,250***	-17,718***	-19,388***
	(1,544)	(1,529)	(1,496)	(1,478)
4.r_stories	-27,857***	-19,463***	-15,930**	-17,486***
	(6,962)	(6,877)	(6,568)	(6,607)
5.r_stories	-84,176***	-59,928***	-47,596***	-50,994***
	(3,162)	(3,727)	(3,588)	(3,594)
6.r_stories	-4,064	-17,377	-30,049	-30,181
	(51,193)	(50,321)	(47,890)	(48,253)
Finished basement	17,912***	17,638***	15,142***	15,191***
	(1,411)	(1,387)	(1,330)	(1,339)
Contaminated Vs Non-Contaminated	-11,882***	-12,371***	-11,505***	-11,221***
	(2,733)	(2,688)	(2,562)	(2,578)
Constant	34,508***	-36,033	10,899	15,145***
	(4,036)	(50,275)	(47,935)	(3,440)
Observations	7,879	7,879	7,879	7,879
R-squared	0.598	0.612	0.649	0.643
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A2.7: Full model results for Table 3, Panel G.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	16,715***	18,658***	20,415***	21,388***
	(1,657)	(1,530)	(1,479)	(1,476)
Living area (sq. ft.)	73.28***	70.99***	68.60***	68.94***
	(1.438)	(1.329)	(1.275)	(1.283)
House age (years)	-491.6***	-260.3***	-363.9***	-372.6***
	(21.22)	(20.77)	(21.81)	(21.10)
Number of bedrooms	10,132***	9,306***	7,946***	8,551***
	(904.3)	(831.6)	(802.3)	(803.9)
Number of full bathrooms	13,421***	9,033***	9,694***	9,388***
	(1,278)	(1,179)	(1,136)	(1,143)
Number of half bathrooms	13,044***	10,917***	9,875***	10,025***
	(1,274)	(1,171)	(1,121)	(1,127)
2.r_stories	-10,046***	-6,779***	-9,157***	-8,026***
	(2,527)	(2,320)	(2,232)	(2,242)
3.r_stories	-25,158***	-21,303***	-16,904***	-18,390***
	(1,571)	(1,452)	(1,421)	(1,407)
4.r_stories	-24,196***	-19,162***	-15,775**	-17,193***
	(7,095)	(6,538)	(6,253)	(6,289)
5.r_stories	-58,155***	-56,049***	-44,116***	-47,349***
	(3,210)	(3,575)	(3,445)	(3,451)
6.r_stories	25,068	-12,297	-26,601	-26,888
	(54,366)	(49,877)	(47,531)	(47,878)
Finished basement	19,449***	17,871***	15,335***	15,428***
	(1,461)	(1,341)	(1,288)	(1,296)
Contaminated Vs Non-Contaminated	-10,515***	-8,755***	-8,292***	-7,930***
	(2,644)	(2,429)	(2,320)	(2,333)
Constant	24,856***	-40,011	20,895	24,255***
	(3,957)	(28,959)	(47,569)	(3,264)
Observations	8,622	8,622	8,622	8,622
R-squared	0.551	0.623	0.658	0.653
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix A3: Full model results for Table 4.

VARIABLES	(1) Year	(2) PWS	(3) MP	(4) SD
Lot size (acres)	12,377***	16,702***	17,701***	17,570***
	(1,068)	(1,069)	(1,068)	(1,054)
Living area (sq. ft.)	102.9***	100.9***	96.68***	97.53***
	(1.094)	(1.077)	(1.068)	(1.066)
House age (years)	-639.8***	-622.5***	-577.8***	-598.2***
	(15.58)	(15.86)	(17.81)	(16.37)
Number of bedrooms	4,479***	5,093***	3,917***	4,379***
	(758.6)	(746.6)	(737.8)	(737.4)
Number of full bathrooms	14,734***	14,294***	14,505***	14,201***
	(968.5)	(953.2)	(939.5)	(940.1)
Number of half bathrooms	3,222***	2,429**	2,029**	2,378**
	(997.9)	(982.0)	(965.8)	(965.9)
2.r_stories	-29,892***	-29,071***	-26,920***	-25,648***
	(3,214)	(3,160)	(3,118)	(3,123)
3.r_stories	-20,216***	-19,587***	-17,080***	-17,804***
	(1,164)	(1,143)	(1,147)	(1,130)
4.r_stories	-35,846***	-35,041***	-29,011***	-30,272***
	(9,672)	(9,508)	(9,312)	(9,344)
5.r_stories	-58,223***	-61,021***	-60,679***	-61,021***
	(3,631)	(3,575)	(3,560)	(3,510)
Finished basement	18,696***	16,942***	16,528***	16,347***
	(1,022)	(1,008)	(993.2)	(992.8)
Contaminated Vs Non-Contaminated	-10,480***	-11,124***	-10,614***	-10,980***
	(2,097)	(2,062)	(2,015)	(2,022)
Constant	8,244***	-5,948**	18,823***	-81,836*
	(2,847)	(2,913)	(4,678)	(43,632)
Observations	18,446	18,446	18,446	18,446
R-squared	0.740	0.749	0.762	0.759
Year FE	Y	Y	Y	Y
PWS FE		Y	Y	Y
Municipality FE			Y	
School District FE				Y

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

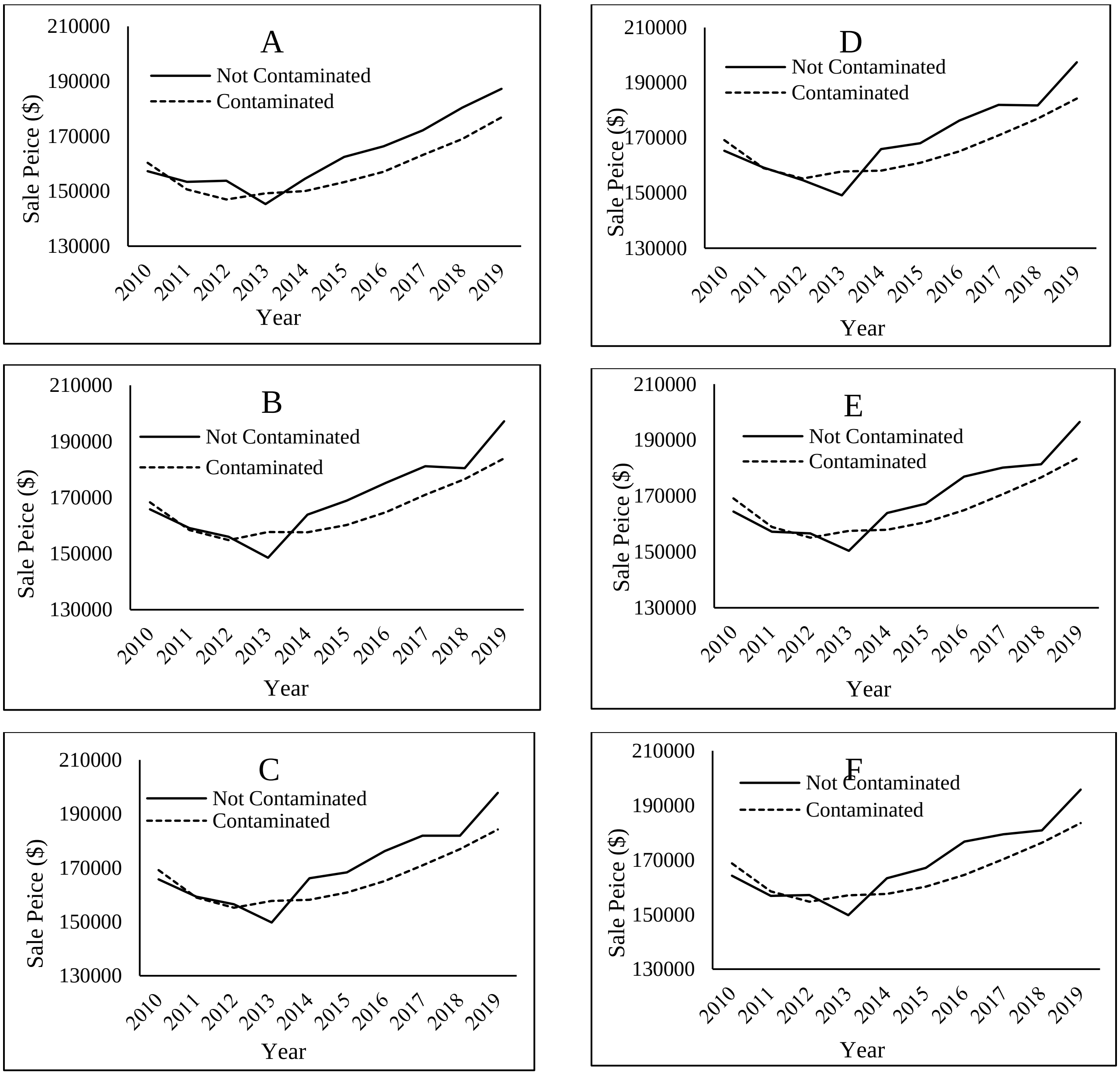
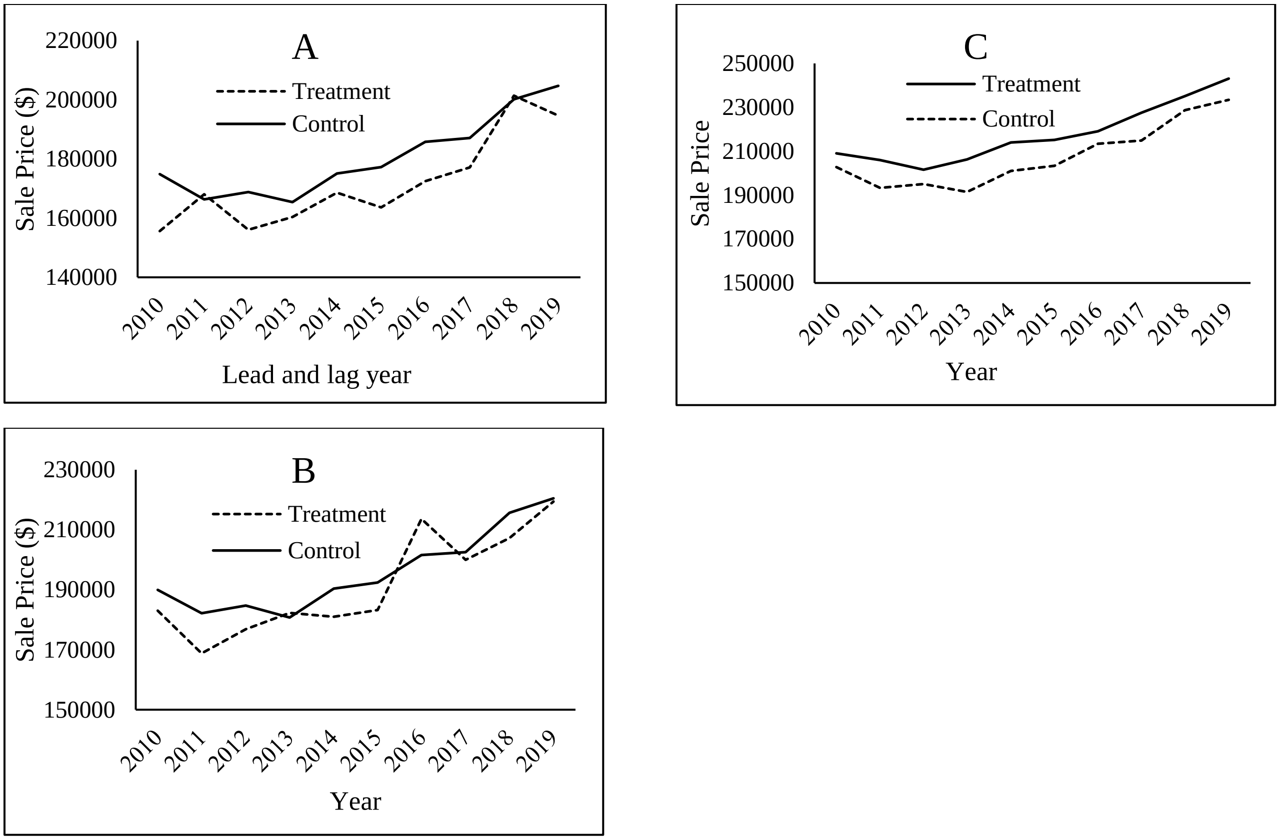
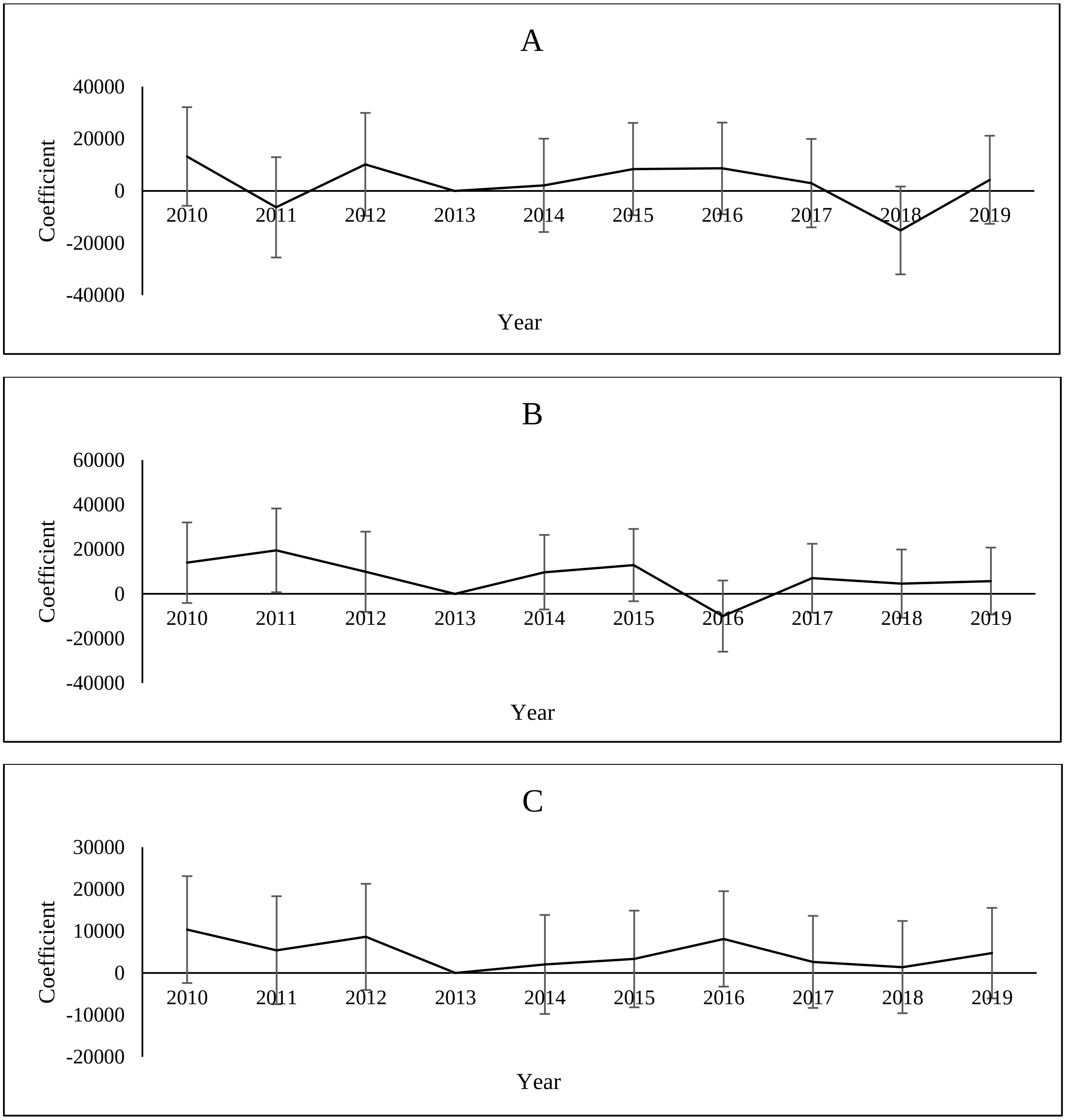


Figure F1: House Price Trends in Contaminated Public Water Systems (PWS) in Dauphin County and Surrounding Areas - one mile (panel A), two mile (panel B), three mile (panel C), four mile (panel D), five mile (panel E), and 10 mile (panel F) outside the 2-mile buffer of contaminated PWS in Dauphin County.



Appendix F2.1: Home price trend in control and (artificial) treatment. Control group is transaction outside the 2-mile boundary for all specification whereas artificial treatment groups are (i) private well dependent houses located outside the 2-mile boundary in Dauphin (panel A), (ii) private well dependent houses in Cumberland (panel B), and (iii) PWS dependent houses in Cumberland (panel C).



Appendix F2.2: Event study graph showing home price trend in artificial treatment groups as compared to the true control group in placebo test specification. For Panel A private well dependent houses located outside the 2-mile boundary in Dauphin is treatment group, for panel B private well dependent houses in Cumberland as treatment and for panel C dependent houses in Cumberland as treatment.