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Contaminated Groundwater: Uncovering the Effects on Home Values

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ABSTRACT:

About 15% of the United States population (43 million people) rely on private wells for their primary source of potable water, and yet (in contrast to public water systems), no routine contaminant monitoring and water treatment is required. Water testing can be expensive, and the need for routine testing may often be unknown to residents, thus allowing potentially harmful water contaminants to go undetected. As such, estimates of the potential effects on households are needed to inform policies and programs to maintain safe potable groundwater wells. We attempt to help fill this gap by estimating hedonic property value models of homes in the Orlando, Florida Metropolitan Statistical Area. We link home transactions to home-specific private well tests conducted by the Florida Department of Health. We find that homes with groundwater well contamination experience a roughly 7% decline in value, and that this decrement persists for many years.

Keywords: contamination; drinking water; groundwater; hedonic; housing; private well

JEL Codes: D6; Q51; Q53; R2

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1. INTRODUCTION

Groundwater is a critical resource in the United States and is a source of potable water for a large portion of the U.S. population. About one-third of the U.S. population (over 102 million people) get their drinking water from public water systems that utilize groundwater (CDC, 2022), and approximately 43 million Americans (about 15% of the population) rely on private groundwater wells for their drinking water (WRMA, 2019; CDC, 2022). Although public water systems are regulated under the Safe Drinking Water Act, with the water quality routinely monitored and treated as needed, no such requirements are in place for private groundwater wells (EPA, 2025). Private residents are generally responsible for any testing and treatment of their well water. Roughly 1 in 5 private wells are estimated to contain at least one chemical at a level that could significantly impact human health (CDC, 2024a, 2024b). The current literature identifies behavioral, situational, and financial barriers that significantly hinder the testing of water quality in private wells, along with a socioeconomic disparity between those that do and do not test (Zheng and Flanagan, 2017; Institute for the Environment, 2023).

It is important to gauge the social welfare implications from such a potentially large public and environmental health issue. Hedonic property value methods are one nonmarket valuation technique that is capable of providing insights, especially given that private wells and the resulting water quality are explicitly part of the housing bundle that impacted households choose.

Despite the potential for hedonic pricing methods in this context, there are few studies examining the implicit losses placed on diminished groundwater well quality. This gap in the literature has largely been attributed to a lack of appropriate data and difficulties with linking measures of groundwater quality to individual homes (McCormick, 1997; Case et al., 2006; Boyle et al., 2010; Guignet, Walsh and Northcutt, 2016). The results of well tests are typically not public information, so distance to pollution sources or spatially aggregated measures of groundwater quality are often used as proxies.

Our objective is to help fill this gap in the literature by conducting a hedonic property value study focused on the Orlando, Florida Metropolitan Statistical Area (MSA); where using a detailed dataset of home transactions from 1990 to 2013, we were able to link each transaction to individual, home-specific private groundwater well tests taken by the Florida Department of Health. In rural parts of the Orlando MSA, pesticide and fertilizer run-off from orange groves and other agricultural activities are a prominent source of groundwater pollution (Guignet, Walsh and Northcutt, 2016; Florida Springs Council, 2023). In more urban areas, the pollutants of concern are more often those associated with leaking underground storage tanks (like those at gas stations), and other types of commercial and industrial activities (FLDEP, 2020; FLDOH 2025). We set out to answer the following three research questions: (1) how does contamination in a private well affect the value of the home? (2) Are any adverse price effects greater in magnitude when the level of contamination is above the corresponding regulatory standard for public water systems? And (3) if there exist any adverse price effects, do these effects diminish or persist over time?

We discuss some common data limitations in the context of groundwater quality and potable wells, including non-random water test sampling, measurement error, and small sample sizes. We address or attempt to circumvent these issues by focusing our analysis only on the subset of homes that were tested before sale, utilizing home-specific well tests, and examining variation based solely on the results of those water tests. We employ matching algorithms to minimize the need for highdimensional spatial fixed effects. Although the inclusion of spatial fixed effects is one of the most common approaches for controlling for spatially correlated confounders in the hedonic literature (Guignet and Lee, 2021), it requires greater sample sizes – an econometric luxury that is often not available in the context of hedonic models and groundwater pollution. Caution is warranted when interpreting our results, but we do generally find that the presence of contamination in a home's potable well is associated with a roughly 7% decrease in home value, and that this effect seems to persist many years after contamination was identified. We find no additional decline in home value when contamination levels are above the corresponding regulatory standard for a particular chemical in public water systems. The mere presence of pollutants in a potable well may be what drives any subsequent decline in home values.

2. LITERATURE REVIEW

There is a large literature on the capitalization of environmental commodities in housing values, but the body of research on the impact of groundwater contamination on property values remains sparse. Historically, much of the research using hedonic price analysis to study the impact of water quality focused on surface water. David's (1968) report was perhaps the first applied study to estimate the effects of surface water quality on home values. The literature then continued to develop, first focusing on lake water clarity in the northeastern U.S. (Michael, Boyle and Bouchard, 2000; Poor et al., 2001; Gibbs, Halstead and Boyle, 2002), and then expanding to other types of waterbodies (Artell, 2013; Netusil, Kincaid and Chang, 2014; Kung, Guignet and Walsh, 2017; Walsh et al., 2017), measures of water quality (Bin and Czajkowski, 2013; Walsh and Milon, 2015), and study areas (Poor, Pessagno and Paul, 2007; Walsh, Milon and Scrogin, 2011). Nationwide primary hedonic studies (Keiser and Shapiro, 2019; Moore et al., 2020; Mamun et al., 2023) and meta-analyses (Guignet et al., 2022) examining the capitalization effects of surface water quality have also emerged. Although there is some mixed evidence, this literature overwhelmingly suggests that diminished water quality in nearby waterbodies does lead to decreases in home values.

Housing price premiums associated with surface water quality are likely driven primarily by aesthetics and corresponding recreational services. This is not likely the case for groundwater and potable water quality, where the provided water is primarily for potable uses (e.g., drinking, bathing, cooking). Studies examining the capitalization effects of groundwater and/or drinking water quality in home prices are much scarcer.

Although our focus in the current study is on private groundwater wells, there is a related area of the hedonic literature focused on the quality of drinking water from public water systems. For example, Des Rosiers, Bolduc and Theriault (1999) studied the effect of drinking water quality on property values in Charlesbourg of Quebec City, and found that among higher-valued homes the presence of water-related health hazards was associated with a 5-10% decline in value. Theising (2019) focused on lead contaminated drinking water and found a 3-4% appreciation following the replacement of lead service lines. Alzaharani and Collins (2022) studied the effect of public water supply unreliability, based on the issuance of boil water notices, and found marginal price declines ranging from 0.6-8.4% due to an additional day of being under a boil water notice. Alzaharani and Collins also find that these price effects are greatest among homes in the lower-end of the price distribution. Christensen, Keiser and Lade (2023) examined the switch of the Flint, Michigan drinking water supply from the Detroit water system to the Flint River, which led to subsequent lead contamination issues. They found an overall decrease in home value of 27-30% after the water supply switch and subsequent emergency declaration. Home prices in Flint remained lower even after 16 months following an announcement that the water was safe to consume. Most recently, researchers have focused on perfluoroalkyl and polyfluoroalkyl substances (PFAS) detected in drinking water. For example, Marcus and Mueller (2024) found a 31-42% depreciation in home values upon discovery of PFAS contamination. A working paper by Khanal and Elbakidze (2024) suggests a $10,000 decrease in home value when serviced by a public water system impacted by PFAS contamination.

Our current study focuses on how contamination in private potable groundwater wells affects home values. Despite being a glaring public health issue, there is little research on how groundwater well quality affects home values. Early studies (Malone and Barrows, 1990; Page and Rabinowitz, 1993; Dotzour, 1997) found no significant relationship between contaminated ground water and property values. While the contributions of these studies are significant, data scarcity and dated econometric identification strategies limit the usefulness of their results. Other studies such as Case et al. (2006) and Boyle et al. (2010) find significant decreases in property values with the presence of contaminated groundwater; however, data constraints required both studies to rely on spatially aggregated measures of contamination. McLaughlin (2011) assesses the disclosure of information regarding contamination, and finds a 7.6% decline in the median home price. Focusing on cases of petroleum releases from underground storage tanks at gas stations, and data gathered on individual, home-specific private well tests, Guignet (2013) found an average 11% reduction in home value when a home's well was simply tested for contamination. Guignet emphasizes that acquiring such home-specific well test data required numerous hours of reviewing hard-copy, paper case files; thus further underscoring the lack of widely available parsed and granular well water data. Focusing on a subset of the study area and data used in our current study, Guignet, Walsh and Northcutt (2016) examined private well tests in Lake County, FL and found a 2-6% depreciation in home values when a home's well was tested and found to be contaminated. Acquisition of house-specific groundwater well test data is rare, and as noted by both Guignet (2013) and Guignet, Walsh and Northcutt (2016), even when such data are available, it cannot often be easily merged to property transaction data and the resulting sample size is small, making econometric analysis challenging.[1]

Ultimately, our current study aims to build upon the small body of research examining the effects of groundwater contamination on home values. To do so, we take advantage of home-specific

[1] Due to these difficulties, a related literature focuses on how home values near sources of pollution change after contamination and/or cleanup events (Messer et al., 2006; Muehlenbachs, Spiller and Timmins, 2015; Haninger, Ma and Timmins, 2017; Guignet et al., 2018; Cassidy, Hill and Ma, 2022; Guignet and Nolte, 2024). Although the estimated capitalization effects from these studies likely reflect groundwater contamination, they also likely reflect other changes at these sites and pollution more broadly. Put another way, the use of proximity and discrete events at these sites provide only a coarse measure of groundwater contamination.

private well tests and results that were linked to individual homes and transactions across the Orlando, Florida MSA.

3. DATA

Our analysis focuses on arms-length transactions of single-family homes in the Orlando, Florida MSA, which consists of Orange, Lake, Osceola, and Seminole counties. Florida is particularly vulnerable to ground water contamination because the state is largely characterized by a high groundwater table, and a thin layer of surface soil with a porous limestone subsurface (Irwin and Bonds, 1987). Home transaction data were compiled from each individual county's property tax assessor offices. Data on potable well tests at individual homes were obtained from the Florida Department of Health (FLDOH). Our study period covers home transactions from 1990 through 2013 because this is the common period for which our two datasets overlapped, and thus where we could link the groundwater well tests to individual home transactions. We carefully matched tests at private potable wells to corresponding home transactions using an address-matching algorithm that linked wells to parcels based on similar address fields and spatial matching that exploited the relationship between well coordinates and parcel boundaries. The text string and location matching techniques were used together to provide the most accurate and comprehensive links possible between the two datasets.[2]

In more rural areas of the Orlando MSA, the pollutants of concern stem primarily from agricultural runoff (Guignet, Walsh and Northcutt, 2016), but in more urban areas the most pressing contamination issues are associated with commercial and industrial activities. In our dataset, nitrogen pollution is by far the most commonly detected contaminant. Nitrates are widely linked to runoff of agricultural fertilizers (Chen et al., 2001; Harrington, Maddox and Hicks, 2010; Solo-Gabriele et al., 2003; EPA, 2024a, 2024b). Different types of trihalomethanes (THMs), including chloroform and bromodichloromethane, are also commonly detected, followed by arsenic, methyl tert-butyl ether (MTBE), and benzene. THMs are often found in water as a byproduct of disinfectant processes (FLDOH, 2024; EPA, 2024a, 2024b). Arsenic can be naturally occurring but has also been historically used in agriculture (as a pesticide and herbicide), and is used in various industrial processes (IARC, 2012; Reigart and Roberts, 2013). MTBE and benzene in groundwater are often linked to leaking underground storage tanks, like those at gas stations, and the latter is also used as a solvent in a variety of industrial processes (Wilson et al., 2013; SWRCB, 2017; NCBI, 2025).

Our well tests data are by no means a random, representative sample. FLDOH regularly tests ground water wells for contamination for a variety of reasons, but most frequently such tests occur because the Florida Department of Environmental Protection (FLDEP) notifies FLDOH of a potential contamination issue caused by human activity. FLDOH must then ask the property owner for permission to test the well, and cannot test it without consent. These two requirements for a

[2] Our home transaction and well test data matching procedure follows that of Guignet, Walsh and Northcutt (2016). Further details of the procedure can be found in the Appendix of their earlier working paper (Guignet, Walsh and Northcutt, 2015).

test to occur, and a contamination measurement to be observed in our data, suggest potential endogenous selection concerns. We address such selection bias concerns by restricting the dataset to only home sales where the private well had been tested prior to sale. Our empirical comparisons are only of homes where the FLDOH identified a potential contamination issue, and where homeowners agreed to testing. Among this subset of home sales, we then compare homes where contamination was or was not discovered, thus circumventing the two main sources of endogenous selection described above. Although this procedure increases the internal validity of our results, we emphasize that external validity is reduced. Nonetheless, given the dearth of nonmarket valuation studies on groundwater quality, we judge this as an appropriate tradeoff and first step.

Initially, 3,908 home transactions were linked to at least one private well test event. Focusing only homes tested *prior to* the transaction, yields a sample of n = 1,566 observations. The majority of these sales pertain to Lake County (753), where runoff from orange groves and other agricultural activities are a primary concern (Guignet, Walsh and Northcutt, 2016), followed by Orange County (530), which is the most urban and includes the City of Orlando, and then Seminole and Osceola Counties (208 and 75, respectively).[3] Descriptive statistics are presented in Table 1. The average home sold for a price of $268,695, has an interior square footage of 2,073, 2.3 bathrooms, is about 21 years in age, and is on a 1.8-acre lot. Note that distribution of acreage is skewed, and that the median lot is only about 0.7 acres. About 7% of the homes are in a 100-year floodplain, and among those where data are available, about 12% of the homes are along the waterfront (usually a lake or connected waterway).

Table 1. Descriptive statistics of home transactions tested prior to sale.

Variable	Obs	Mean	Std. dev.	Min	Max
Price (2013$ USD)	1,566	268,695	176,644	16,053	2,982,041
Above DL	1,566	0.663	0.473	0	1
Above STD	1,566	0.184	0.388	0	1
Square Footage	1,544	2,073	842	384	6,063
Missing: Square Footage	1,566	0.014	0.118	0	1
Total Baths	1,544	2.33	0.88	1	6.8
Missing: Total Baths	1,566	0.014	0.118	0	1

[3] Prior to linking the well test data, the home transaction data were cleaned to focus on full arms-length transactions of single-family homes between 1990-2013. Transactions where the home was recorded as having more than twelve bathrooms or was on a lot exceeding 50 acres were excluded, as were sales for which the real price was in the top or bottom percentiles for each respective county. The corresponding sample sizes were 124,859 transactions in Lake County, 447,235 in Orange, 212,240 in Seminole, and 139,562 in Osceola. The full sales datasets were not used in our analysis due to the potential for unobserved systematic differences between the broader set of homes and those with groundwater well contamination. For example, among the broader set of homes, we cannot firmly establish which rely on a private well for potable water versus those connected to the public water system. In some areas of Florida, even homes within the public water service areas rely on private wells (Guignet, Walsh and Northcutt, 2016). This concern is in addition to the aforementioned biases due to the non-random testing of wells in our FLDOH data. Therefore, our analysis focuses only on transactions where the private potable well at the home was tested prior to the sale. It is among these transactions that we can be sure the homes do rely on private potable wells, and also where we can circumvent biases from the non-random, targeted well testing by the FLDOH.

Acres	842	1.84	2.21	0.13	13.94
Missing: Acres	1,566	0.462	0.499	0	1
Age	1,520	21.26	18.34	0	135
Missing: Age	1,566	0.029	0.169	0	1
Waterfront	979	0.122	0.327	0	1
Missing: Waterfront	1,566	0.375	0.484	0	1
Floodplain	1,566	0.067	0.250	0	1

Among these home transactions where the FLDOH tested the potable groundwater well prior to the sale, we see that about 66% had a test reveal contamination above the detectable limit (DL), meaning that contamination was present. And among 18% of the home transactions, the tests revealed contamination where the concentration of one or more chemicals was above the regulatory standard (STD) for public water systems – i.e., the corresponding Federal Maximum Contaminant Level (MCL) under the Safe Drinking Water Act or the State of Florida's health advisory level (HAL).

As discussed in the next section, our primary models further restrict the sample to only homes tested within three years prior to the transaction. The three-year temporal window is based on precedent in the literature (Boyle et al., 2010; Guignet, Walsh and Northcutt, 2016), and facilitates comparison of the results, but was also chosen based on considerations of sample size and accuracy of the measured contamination levels. A broader temporal window allows for a larger sample, but as the date of the well test extends farther back in time, the less accurate the recorded contamination levels may be relative to when the home was sold. A smaller temporal window focuses on more recent, and presumably more accurate test results relative to the time of sale, but will result in a smaller sample size.[4] In our later analysis, we investigate how are results vary based on different assumed temporal windows, ranging from tests within one year of a transaction, out to any time prior to a transaction.

4. METHODS

We estimate a series of hedonic price models of the following form, where $ln(p_{ijt})$ is the natural log of the price of home i, in neighborhood j, sold in period t. In our most comprehensive models, the independent variables include a vector of characteristics of the home and its location $\boldsymbol{x_{ijt}}$ (i.e., interior square footage, number of bathrooms, lot acreage, age, and whether the home is on the

[4] Such small sample size concerns are exacerbated after utilizing our empirical matching algorithm, which is employed to yield a more similar distribution of homes with and without a contaminated well, and ultimately to more cleanly identify any house price effects associated with groundwater well contamination (see Section 4 for details). As shown in Figure A1 in the Appendix, the matched sample sizes range from just 172 observations when focusing on homes tested one year prior to a transaction, up to only 539 observations when focusing on homes tested any time before their transaction.

waterfront or in a floodplain), separate year and quarter fixed effects $\boldsymbol{\varphi_t}$, and spatial fixed effects θ_j, which are usually – due to small sample sizes within a tract – at the county-level.[5]

$$ln(p_{ijt}) = \boldsymbol{x_{ijt}\beta} + \boldsymbol{\varphi_t} + \theta_j + \gamma^{DL} AboveDL_{ijt} + \varepsilon_{ijt} \quad (1)$$

The last term ε_{ijt} is a normally distributed disturbance term. The parameters to be estimated are $\boldsymbol{\beta}$, $\boldsymbol{\varphi_t}$, θ_j, and of primary interest, γ^{DL}. The latter coefficient corresponds to the binary indicator $AboveDL_{ijt}$, which equals one if any of the contaminants tested for are found to be present in the well water (i.e., at levels equal to or above the detectable limit); and zero otherwise. Therefore, γ^{DL} captures the association between home prices and having a contaminated potable groundwater well.

In subsequent models, we examine whether any association between groundwater contamination and home values vary based on whether the levels of any detected pollutants are above the corresponding Federal MCL or the state of Florida's corresponding HAL. This is done by adding an additional term equal to one when at least one tested contaminant is at levels above the corresponding standard $AboveSTD_{ijt}$; and zero otherwise. The corresponding coefficient γ^{STD} captures any additional price difference associated with contamination levels above the corresponding regulatory standard, relative to a home with contamination but at levels below any standards.[6]

$$ln(p_{ijt}) = x_{ijt}\beta + \varphi_t + \theta_j + \gamma^{DL} AboveDL_{ijt} + \gamma^{STD} AboveSTD_{ijt} + \varepsilon_{ijt} \quad (2)$$

To circumvent issues with the non-random selection and timing of potable water tests conducted by the FLDOH, we estimate equations (1) and (2) using only homes that were tested prior to the sale (see Section 3 for details). The basic premise is that conditional on being tested, the results of the well water tests could be considered exogenous. Although limiting our sample in this fashion may limit the external validity of our results, it does help us better isolate any price decrement associated with having a contaminated groundwater well.

To further ensure a comparable counterfactual, in later models we carry out an exact covariate matching procedure, where we match transactions of homes tested prior to their sale that did $(AboveDL_{ijt} = 1)$ and did not $(AboveDL_{ijt} = 0)$ have contamination. This matching procedure was carried out using Coarsened Exact Matching (Blackwell et al., 2009; Iacus, King and Porro, 2012), although we specified exact matches for all included covariates. Matching provides a flexible approach to yield a more comparable sample of home sales with and without groundwater contamination (Blackwell et al., 2009; Iacus, King and Porro, 2012). Exact matches were determined based on county, the year and quarter of the transaction, and how many years the test

[5] As noted in Section 3, the sample starts with just 1,566 sales, and this is reduced even further after the sample matching procedures discussed later in this Section. Figure A1 in the Appendix shows the matched sample sizes across various assumptions for the assumed timeframe for which well tests may affect home values. Under our main specifications that consider well tests up to three years prior to a transaction, the sample entails just 325 transactions.
[6] These regulatory standards pertain to public water systems, and do not apply to private groundwater wells. Nonetheless, the corresponding chemical concentrations may signal elevated health risks to homeowners whose water is found to have higher levels of contamination.

took place prior to the sale. Matched "treated" group sales with $AboveDL_{ijt} = 1$ are given a weight of one, and any matched counterfactual sales $\left(AboveDL_{ijt} = 0\right)$ are given a positive weight that may be less than or equal to one, depending on how many "treated" sales it was matched to, and how many other "control" sales were matched to the corresponding "treated" sales. If a counterfactual home sale is matched to multiple "treated" home sales, then it may be given a weight greater than one. The weights are used to estimate equations (1) and (2) via Weighted Least Squares, and so the matching algorithm essentially "constructs" a counterfactual uncontaminated home transaction for each contaminated home transaction as a weighted average of all matched counterfactual homes. The basic intuition is that we are matching and comparing homes sold in the same county, during the same year and quarter, *and* where both homes were tested around the same time (Y years earlier relative to the sale date), but where one of the tested homes did not have contamination in the potable well and the other did.

To interpret the results corresponding to the $AboveDL_{ijt}$ and $AboveSTD_{ijt}$ indicators as percent changes in price, we carry out the below post-regression calculations (Halvorsen and Palmquist, 1980):

$$\%\Delta p\ AboveDL = \{exp(\gamma^{DL}) - 1\} \times 100 \tag{3}$$

$$\%\Delta p\ AboveStd = \{exp(\gamma^{DL} + \gamma^{Std}) - 1\} \times 100 \tag{4}$$

where $\%\Delta p\ AboveDL$ denotes the percent change in home price when the potable well is contaminated, and $\%\Delta p\ AboveSTD$ reflects the percent change in price when the levels of contamination for at least one tested chemical are above the corresponding health-based regulatory standard. Both of the estimated price changes are relative to homes that were tested, but where no detectable levels of contamination are found.

We hypothesize that $\%\Delta p\ AboveSTD < \%\Delta p\ AboveDL < 0$. In other words, consistent with previous research (Case et al., 2006; Boyle et al., 2010), we expect that the presence of contamination in a potable well is associated with a decrease in home values. We also expect that this negative association is greater in magnitude when contaminant levels are above the corresponding regulatory standard.

5. RESULTS

For the first set of results, we limit the sample to only homes that were tested within three years prior to the transaction. This initial temporal window of three years is chosen for comparison to previous groundwater studies (Boyle et al., 2010; Guignet, Walsh and Northcutt, 2016), and as discussed in Section 3, is based on a tradeoff between a larger sample size when considering a greater temporal window, versus possible measurement error between contamination levels when a test is taken and at the time of sale.

The estimated percent changes in price following equations (3) and (4) are shown in Table 2. Models 1 and 2 in Table 2 are estimated using the full sample of n=764 home sales where the home was tested within three years prior to the sale. Model 1 includes no independent variables, and provides a baseline association between groundwater well contamination and home values. Model 2 includes all year, quarter, and county fixed effects, as well as the full suite of house and location attributes. The full regression results are shown in Table A1 in the Appendix, and generally suggest the expected sign and significance for the coefficient estimates that are not of primary interest. Interior square footage and lot acreage positively contribute to the price of a home, and the negative quadratic parameters suggest a diminishing marginal implicit price. The number of bathrooms and being on the waterfront are also highly significant and positively correlated with house prices, whereas the age of the home exhibits a negative relationship. Being in a floodplain is associated with an increase in price, and likely reflects unobserved amenities associated with being near waterbodies (Michael, Boyle and Bouchard, 2000; Poor et al., 2001; Gibbs, Halstead and Boyle, 2002).

Models 1 and 2 in Table 1 suggest a 4-6% decrease in home value when the potable well is contaminated, but these estimates are statistically insignificant. The remaining models in Table 1 are estimated using the matched sample of 325 home sales – 181 of which had $AboveDL_{ijt} = 1$, and 144 with $AboveDL_{ijt} = 0$. Model 3 includes no additional covariates or fixed effects on the right-hand side. Separate year and quarter fixed effects are added to Model 4 in order to further control for broader housing market trends and seasonal effects over time. Both models suggest a statistically significant 13.4% decrease in value when a home's well is contaminated. Model 5 includes the house and location attributes, and suggests a lower magnitude but still significant 7.3% price decrease associated with a contaminated potable well. This result is robust to the addition of county fixed effects in Model 6, leading to the general conclusion that potable well contamination within the preceding three years is associated with a 7.4% decline in the value of a home.

Table 2. Percent changes in price associated with groundwater well contamination within preceding three years.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Above DL %ΔP	-5.93	-4.04	-13.43**	-13.43**	-7.28**	-7.40**	-8.17**
	(4.70)	(3.19)	(6.74)	(6.31)	(3.51)	(3.51)	(3.65)
Above STD %ΔP							-4.04
							(7.54)
Year and Quarter FE		X		X	X	X	X
Covariates		X			X	X	X
County FE		X				X	X
Matched Sample			X	X	X	X	X
Observations	764	764	325	325	325	325	325
Adjusted R-squared	0.001	0.638	0.010	0.072	0.754	0.752	0.751

Note: Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Percent change in price calculations based on equations (3) and (4). See Table A1in the Appendix for the full hedonic regression results.

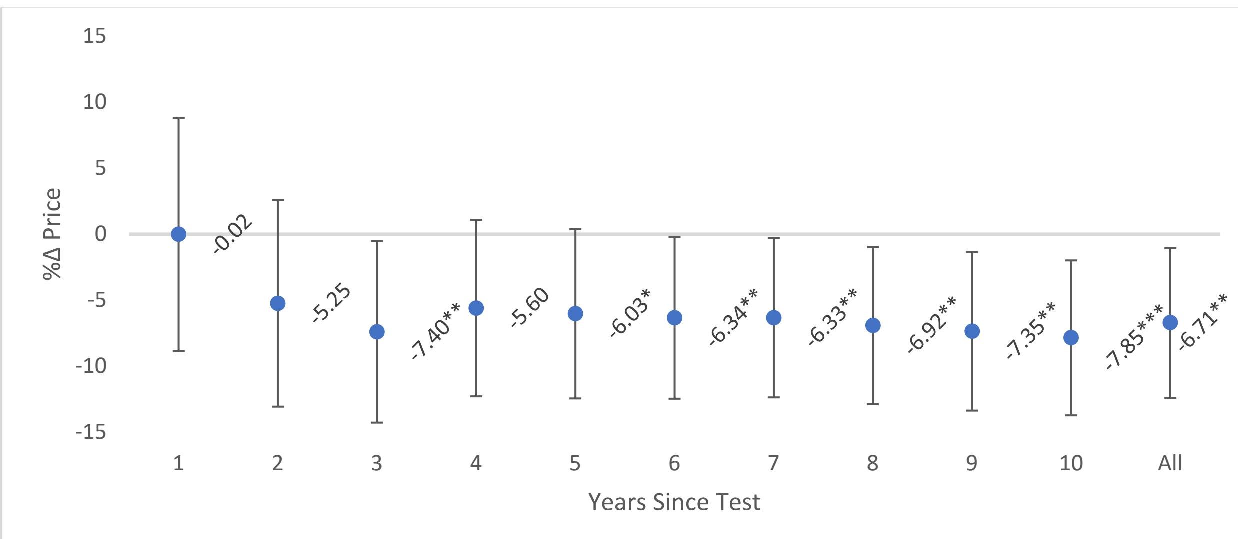
Model 7 in Table 1 further accounts for whether the contamination levels exceeded regulatory thresholds. As shown in Table A1 in the Appendix, the coefficient estimate corresponding to $AboveSTD_{ijt}$ is statistically insignificant, and has a positive sign. Following equation (4), the estimated percent change in price associated with contamination levels above the regulatory standard is very imprecise and statistically insignificant. This goes against our initial hypothesis that any negative association with home values would be stronger at higher levels of contamination, but is consistent with Guignet, Walsh and Northcutt's (2016) earlier study focused on Lake County, FL. We speculate that treatment technologies (e.g., a water filter) are more likely to be put in place when health-based standards are exceeded, and this may partly mitigate the initial decrease in value due to contamination. In any case, it seems that the negative association with home prices is driven by cases where the groundwater well has contamination, but where the pollution levels remain below any health-based standards. This negative association is slightly greater in magnitude under Model 7, suggesting an 8.2% depreciation.

A causal interpretation of our estimated 7-8% decrease in home value associated with groundwater contamination is cautioned. Although we do our best to identify a causal effect by comparing only homes that were tested, employing exact covariate matching, accounting for a slew of key house and location attributes, and by including temporal and county fixed effects, we cannot the rule out the possibility of confounding factors, and in particular, spatially correlated omitted variables. The inclusion of high-resolution spatial fixed effects is one common approach to address spatially correlated confounders (Guignet and Lee, 2021), but such a strategy is not plausible in cases with smaller samples, as is the case here. Furthermore, one must be cognizant of the spatial resolution of the environmental commodity of interest relative to the applied fixed effects (Abbott and Klaiber, 2011). The spatial fixed effects could inadvertently absorb some of the price and pollution variation of interest. That is why we did not go beyond the inclusion of coarser county fixed effects in the main analysis, and instead do our best through matching and by including key locational attributes (i.e., presence in a flood zone and being on the waterfront). Despite our concerns regarding the appropriateness of finer resolution spatial fixed effects, we do examine the sensitivity of our results to the inclusion of higher resolution, Census tract-level fixed effects. The results are presented in Table A2 in the Appendix. We find that private well contamination is associated with a 2.2 to 11.1 percent decline in home value. The results are largely insignificant, however, with the exception of the 11.1% decrease ($p \leq 0.05$) from Model 4′, which excludes the house and location covariates, but includes all temporal fixed effects and is estimated using the matched-sample. Although there are certainly mixed results, we view the tract fixed effect model results as being consistent with our earlier findings.

Thus far our results have been based only on potable well tests and contamination levels detected within the three years prior to the sale of a home. We next examine alternative temporal windows, focusing only on homes tested within 1, 2, 3, … and out to 10 years prior the sale. We also estimate a model that accounts for tests and contamination results *any* time prior to the sale of a home. For this exercise, we focus on variants of our most thorough model, Model 6 (see Table 1).

For each temporal window, we limit the sample to only home sales where a test took place within the corresponding timeframe before the transaction, redo the matching algorithm, and then reestimate the corresponding variant of Model 6. The $\%\Delta p\ AboveDL$ estimates for each model are displayed in Figure 1. The point estimate for year one is practically zero, and is statistically insignificant. It is important to note that the sample size for the model considering tests conducted within just one year prior to a sale is small (n=172). When considering tests within two years of a sale, we see a 5.3% decline, but again, this result is statistically insignificant. Considering tests three years, four years, and so on, prior to the sale of a home, we see estimated declines in home value ranging from a 5.6% to 7.9% decrease in home values. With the exception of just one model (corresponding to tests within four years), these negative associations are statistically significant. Even when considering tests and contamination levels found up to nine or ten years, or even any time before the sale, we see a statistically significant depreciation in value associated with having a contaminated well. This suggests that any negative price effects stemming from groundwater contamination persist over time.

Figure 1. Percent changes in price associated with groundwater well contamination: Estimates across different temporal windows prior to a house sale.



Note: * p < 0.10, ** p < 0.05, *** p < 0.01. Estimates and corresponding standard errors are included in Table A3 in the Appendix.

6. CONCLUSION

Despite about 15% of the U.S. population relying on private groundwater wells as their primary source for potable water (WRMA, 2019; CDC, 2022), and the glaring absence of public health information due to the lack of oversight, monitoring, and data on groundwater contamination, there are few economic studies examining how such contamination may impact home values and household welfare. We help fill this gap by empirically analyzing home-specific groundwater well tests and home transactions in the Orlando, Florida MSA. As hypothesized, the results suggest that home values are reduced by about 7% when a private well is contaminated. Against our initial expectation, this price decrement is less in magnitude and becomes statistically insignificant when focused on wells contaminated at levels above the corresponding State or Federal health-based standards that are in place for public water systems. We speculate that homeowners often take mitigative actions (i.e., install a filter or other treatment device) when their groundwater is contaminated at such high levels, and that this in turn reduces any negative effect on home values. Finally, the results suggest that the price decline associated with the presence of contamination in general do not diminish over time, and persist for many years after the contamination was discovered.

The persistent effect of groundwater contamination on home values are in contrast to findings in other hedonic property value studies (Case et al., 2006; Boyle et al., 2010; Guignet, Walsh and Northcutt, 2016), and may reflect continued contamination issues, or even just a perceived stigma towards the home and surrounding neighborhood (Messer et al., 2006). It is also possible that our groundwater measure is picking up residual, spatially correlated confounders. Despite our efforts to reduce such confounders – by focusing on only tested homes, employing exact covariate matching, and accounting for key house and location attributes, including temporal and county fixed effects – the possibility for an omitted variable bias remains. As such, interpreting our results as capturing a firmly causal relationship is cautioned.

Nonetheless, given the dearth of implicit price estimates in the context of groundwater contamination and home values, as well as the need for researchers to often rely on spatially coarse measures of water quality, our estimated 7% decline in value associated with groundwater contamination, which is based on home-specific groundwater quality measures, contributes to the literature. With the appropriate caveats, our results are useful in informing policy and programmatic decisions to mitigate groundwater pollution and ensure safe potable water.

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APPENDIX

Figure A1. Sample sizes for matched samples with varying temporal windows for when well test occurred before a transaction.

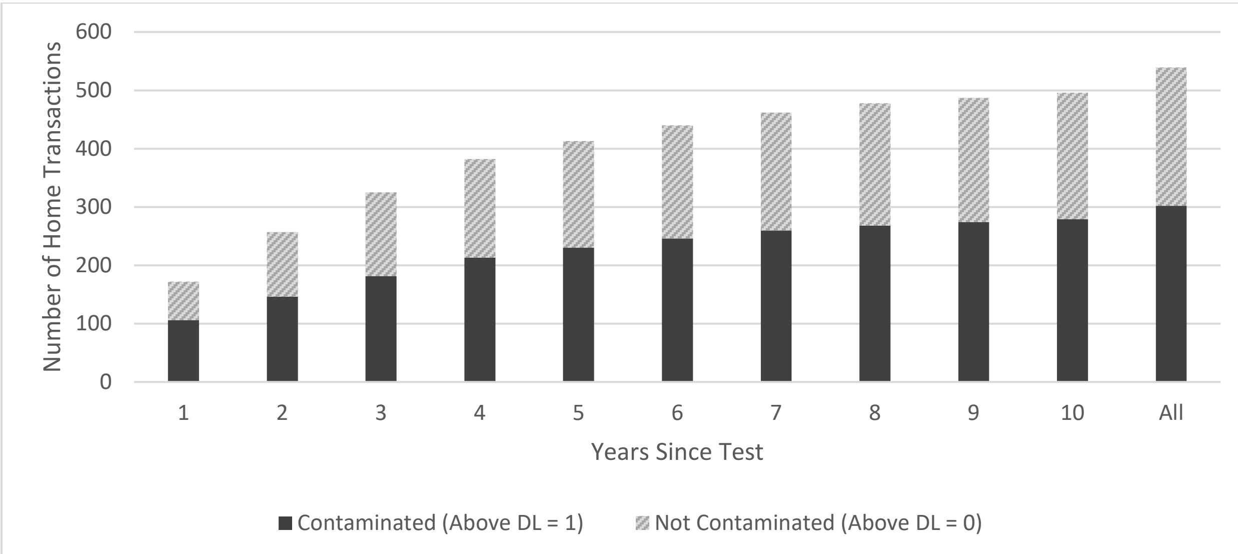

Table A1. Full hedonic regression results: Groundwater contamination within preceding three years.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Above DL	-0.0612	-0.0412	-0.1442*	-0.1442**	-0.0756**	-0.0769**	-0.0853**
	(0.0500)	(0.0332)	(0.0778)	(0.0729)	(0.0378)	(0.0379)	(0.0398)
Above Std							0.0440
							(0.0780)
Square Footage		0.0009***			0.0009***	0.0009***	0.0009***
		(0.0001)			(0.0001)	(0.0001)	(0.0001)
Square Footage^2		-0.0000***			-0.0000***	-0.0000***	-0.0000***
		(0.0000)			(0.0000)	(0.0000)	(0.0000)
Missing: Square Footage		1.8189***			1.2905***	1.2722***	1.2876***
		(0.4226)			(0.3165)	(0.3177)	(0.2958)
Total Baths		0.1295***			0.1163***	0.1099***	0.1119***
		(0.0272)			(0.0332)	(0.0377)	(0.0373)
Acres		0.0813***			0.1005***	0.1062***	0.1110***
		(0.0241)			(0.0264)	(0.0265)	(0.0270)
Acres^2		-0.0031			-0.0040	-0.0045*	-0.0048*
		(0.0024)			(0.0027)	(0.0026)	(0.0027)
Missing: Acres		0.1118**			0.1357***	0.1512***	0.1607***
		(0.0460)			(0.0462)	(0.0501)	(0.0490)
Age		-0.0051***			-0.0076***	-0.0080***	-0.0078***
		(0.0014)			(0.0018)	(0.0023)	(0.0024)
Missing: Age		-1.0051***			-0.0334	-0.0414	-0.0393
		(0.1750)			(0.1114)	(0.1195)	(0.1143)
Waterfront		0.2448***			0.1658***	0.1671***	0.1614**
		(0.0523)			(0.0572)	(0.0607)	(0.0639)
Missing: Waterfront		-0.3506*			0.0186	-0.0003	0.0262
		(0.1844)			(0.0441)	(0.1468)	(0.1572)
Floodplain		0.0754*			0.0701*	0.0638	0.0572
		(0.0404)			(0.0396)	(0.0443)	(0.0440)
Constant	12.2949***	10.2656***	12.4352***	12.3170***	10.1505***	10.1734***	10.2535***

	(0.0412)	(0.0952)	(0.0621)	(0.3154)	(0.1687)	(0.1700)	(0.1715)
Year and Quarter FE		X		X	X	X	X
Covariates		X			X	X	X
County FE		X				X	X
Matched Sample			X	X	X	X	X
Observations	764	764	325	325	325	325	325
Adjusted R-squared	0.001	0.638	0.010	0.072	0.754	0.752	0.751

Note: Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Percent changes in price associated with groundwater well contamination within preceding three years: Tract fixed effects.

	(1')	(2')	(3')	(4')	(5')	(7')
Above DL %ΔP	-6.28	-2.21	-8.42	-11.11**	-5.74	-6.01
	(4.24)	(2.98)	(5.95)	(5.26)	(3.65)	(3.77)
Above Std %ΔP						-4.46
						(7.03)
Year and Quarter FE		X		X	X	X
Covariates		X			X	X
Tract FE	X	X	X	X	X	X
Matched Sample			X	X	X	X
Observations	738	738	293	293	293	293
Adjusted R-squared	0.387	0.747	0.508	0.591	0.831	0.830

Note: Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Percent change in price calculations based on equations (3) and (4). Displayed estimates are variants of Models 1-7 in Table 1, but include higher resolution tract-level spatial fixed effects. Note that the difference between Models 5 and 6 in Table 1 is the inclusion of county fixed effects. Since all models here include tract-level fixed effects, Models 5′ and 6′ are redundant, and only one is included here.

Table A3. Percent changes in price associated with groundwater well contamination: Estimates across different temporal windows prior to a house sale.

Years:	1	2	3	4	5	6	7	8	9	10	All
Above DL %ΔP	-0.02	-5.25	-7.40**	-5.60	-6.03*	-6.34**	-6.33**	-6.92**	-7.35**	-7.85***	-6.71**
	(4.51)	(3.99)	(3.51)	(3.41)	(3.27)	(3.12)	(3.08)	(3.04)	(3.06)	(2.99)	(2.90)
Year and Quarter FE	X	X	X	X	X	X	X	X	X	X	X
Covariates	X	X	X	X	X	X	X	X	X	X	X
Tract FE	X	X	X	X	X	X	X	X	X	X	X
Matched Sample	X	X	X	X	X	X	X	X	X	X	X
Observations	172	257	325	382	413	440	462	478	487	496	539
Adjusted R-squared	0.764	0.756	0.752	0.740	0.731	0.726	0.729	0.728	0.729	0.730	0.716

Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Percent change in price estimates following equation (3), and as displayed in Figure 1. Each estimate is from a separate regression model where the temporal window varies to consider homes where the well was tested within 1, 2, …, 10 years prior to the sale, as well as any year (or "All" years) prior.