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The Property Value Impacts of Groundwater Contamination: Agricultural Runoff and Private Wells

Dennis Guignet, Rachel Northcutt, and Patrick Walsh

Working Paper Series

Working Paper # 15-05
November, 2015

U.S. Environmental Protection Agency
National Center for Environmental Economics
1200 Pennsylvania Avenue, NW (MC 1809)
Washington, DC 20460
http://www.epa.gov/economics

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The Property Value Impacts of Groundwater Contamination: Agricultural Runoff and Private Wells

By:
Dennis Guignet*, Rachel Northcutt, and Patrick Walsh

National Center for Environmental Economics
US Environmental Protection Agency

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Abstract:
There are few studies examining the impacts of groundwater quality on residential property values. Using a unique dataset of groundwater well tests, we link residential transactions to home-specific contamination levels and undertake a hedonic analysis of homes in Lake County, Florida; where groundwater pollution concerns stem primarily from agricultural runoff. We find that testing and contamination yield a 2% to 6% depreciation, an effect that diminishes after the situation is resolved. Focusing specifically on nitrogen-based contamination, we find prices decline mainly at concentrations above the regulatory health standard, suggesting up to a 15% deprecation at levels twice the standard.

*Corresponding Author
National Center for Environmental Economics
US Environmental Protection Agency
Mail Code 1809 T
1200 Pennsylvania Avenue, N.W.
Washington, DC 20460, USA
Ph: 01-202-566-1573
guignet.dennis@epa.gov

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INTRODUCTION

Estimating the value of groundwater resources and the services they provide is a critical component of informing policy decisions on protecting and improving water quality. One of the most crucial services provided by groundwater is that it is an important source of drinking water. In the US, groundwater is the source for 77% of community water systems, and about 15% of the population rely on private groundwater wells as their water source (US EPA, 2012a, 2012b). Private wells are particularly susceptible to potential water quality issues because they are not regulated under the Safe Drinking Water Act, and do not regularly undergo monitoring and treatment to ensure water quality. Furthermore, households relying on private wells tend to be in rural areas, where local aquifers are potentially vulnerable to contamination from nearby agricultural activities.

The hedonic property value method is a natural valuation approach for estimating the welfare impacts from changes in groundwater quality. The private well and the quality of the local groundwater aquifer are inherently linked to the housing bundle, and so a change in quality, at least as perceived by buyers and sellers in the market, should be capitalized in the price of a home. In theory, any property value impacts reflect the change in the present value of the future stream of expected utility a homebuyer expects to derive from the housing bundle. Given the amount of household activities that depend on safe water, a contaminated well should have a direct impact on home prices.

Although there are multiple applications of the hedonic property value approach to surface water quality, there are very few rigorous hedonic studies on groundwater quality. We attribute this gap in the literature largely to the lack of appropriate data and difficulties in linking groundwater quality measures to individual homes. Groundwater well test results are not usually publicly available, so much of the past literature has used distance or aggregated measures as proxies for contamination. Our paper surmounts these data issues through a unique and comprehensive dataset of groundwater contamination tests conducted by the Florida Department of Health (FLDOH). We link residential property transactions to home-specific contamination levels in private potable wells, and undertake a hedonic analysis to examine how property values respond to groundwater pollution. The focus is on Lake County, Florida, where a large proportion of groundwater pollution stems from pesticide and fertilizer runoff from orange groves and other agricultural activities.

To our knowledge this is the first hedonic study to link water quality data in private potable wells to individual homes and have a dataset rich enough to thoroughly examine the relationship between groundwater pollutant concentrations and residential property values. Further, this is the most rigorous hedonic study to date examining the impact of agriculture-related groundwater pollution on residential property values.

Using a dataset of residential transactions from 1990 to 2013, we empirically examine four main hypotheses. First, does groundwater pollution impact home values? Second, if so, how do these price impacts vary over time? Third, do the property value impacts vary depending on the type of contaminant? Fourth, how do these impacts vary with increases in pollutant concentrations?

The next section outlines the existing hedonic literature on water quality and the few studies specifically on groundwater. Then background on agricultural activities and groundwater quality in Florida (and specifically in Lake County) is provided; followed by a discussion of the empirical model and data used to estimate the model. The hedonic regression results are then presented, followed by concluding remarks.

LITERATURE REVIEW

Since Rosen (1974) set the underpinnings that theoretically connect hedonics to welfare analysis, there has been a flurry of hedonic property value studies on a variety of environmental amenities and disamenities.[1] Water quality and property prices have been linked as far back as the 1960's (David, 1968), although water quality monitoring is only recently starting to reach a density conducive to widespread analysis. Since 2000, federal, state, and local monitoring efforts are increasing, along with the corresponding data availability. Several earlier papers that found a significant relationship between water quality and property prices include Michael et al., (2000), Poor et al., (2001), and Gibbs et al., (2002). Much of the literature around that time utilized available water clarity data for northeast US lakes. More recent studies have expanded the type of waterbody analyzed (Artell, 2013; Netusil, Kincaid, & Chang, 2014), the water quality parameter used (Bin & Czajkowski, 2013; P. Walsh & Milon, 2015), and the population affected (Poor, Pessagno, & Paul, 2007; P. J. Walsh, Milon, & Scrogin, 2011). Much of the hedonic literature, however, has focused almost exclusively on surface water quality.

The hedonic literature explicitly examining how groundwater quality impacts residential property values is noticeably thinner, with only a few rigorous studies.[2] Groundwater contamination is often difficult to detect, and if homes are on a public water supply there may be negligible health impacts from local groundwater contamination plumes. In early studies, Malone and Barrows (1990), Page and Rabinowitz (1993), and Dotzour (1997) did not find a significant

[1] M. A. Boyle and Kiel (2001) and Jackson (2001) provide somewhat dated but comprehensive literature reviews.

[2] Several other papers have explored the impact of contaminated groundwater on agricultural parcels, where irrigation is of primary concern (Buck, Auffhammer, & Sunding, 2014).

relationship between groundwater contamination and property prices. These earlier studies offer valuable contributions to the literature, but the econometric identification strategies are now fairly dated, and the groundwater data at the time was relatively scant, leading to issues of small sample sizes and coarse measures of groundwater quality.

More recently, Case et al., (2006) used a hybrid repeat sales/hedonic technique and found a 4.65% price decrease among residential condominiums impacted by groundwater contamination, but only after knowledge of the contamination was public. Although temporary, Boyle et al. (2010) found a significant 0.5% to 1% decline in home values for each 0.01 mg/l of arsenic contamination above the 0.05 mg/l regulatory standard at the time. Due to data constraints both these studies utilized spatially aggregated measures of groundwater contamination.

In contrast, Guignet (2013) compiled a unique dataset of private groundwater well tests, and linked these tests to individual home transactions. These tests serve as a clear signal to households, and provide a clean home-specific measure of the disamenity. Guignet’s results indicated that homes tested for groundwater contamination face a significant 11% decrease in prices, even if the results revealed no contamination. A somewhat larger 13% depreciation was reported when tests revealed contamination levels above the regulatory standard, but caution is warranted in interpreting this result because only ten transactions were observed where contamination exceeded the standard.

The current study builds on these past works by utilizing a rich dataset of groundwater well contamination tests conducted and compiled by the FLDOH for the entire State of Florida from the 1980s through 2013. These data allow us to link groundwater contamination levels in private wells to individual homes, enabling a detailed investigation into how home prices vary with home-specific pollutant concentrations. Further, with the exception of Malone and Barrows (1990), to our knowledge this is the only hedonic study examining how total nitrate and nitrite, along with other contaminants associated with surrounding agricultural activities, affect home values.

BACKGROUND: AGRICULTURE AND GROUNDWATER IN FLORIDA

Approximately 90% of Florida residents depend on groundwater for drinking water (SRWP, 2015). At the same time, Florida is particularly vulnerable to human health effects from groundwater contamination because the hydrology of the state is characterized by a high water table and thin surface layer of soil (SRWP, 2015). Contributing to Florida's increased risk of groundwater contamination are the many point and non-point pollution sources throughout the State, with agriculture-related activities posing a considerable threat (SRWP, 2015).

Florida greatly contributes to overall agricultural production in the US, ranking among the top states in the production of citrus crops and other fruits and vegetables (FLDACS, 2012). In this analysis we focus on Lake County, Florida, which has a long history of citrus farming and other agricultural activities (FLDACS, 2012; Furman, White, Cruz, Russell, & Thomas, 1975). Lake County sits in the central region of the state, and together with its neighboring central Florida counties, produce the majority of Florida's citrus crops (FLDACS, 2012). On its own, Lake County produced the tenth highest volume of citrus crops in Florida, with the eleventh highest acreage devoted to commercial citrus production (FLDACS, 2012). About 5% of the land area (32,207 acres) in Lake County is devoted to citrus groves, and another 5% (30,956 acres) to row crops.[3] Although soils in Lake County are suitable for citrus groves, these soils would not offer

[3] Land areas calculated in a Geographic Information System (GIS) using data obtained from the Florida Fish and Wildlife Conservation Commission (FFWCC), accessed Feb 6, 2015 at http://ocean.floridamarine.org/TRGIS/Description_Layers_Terrestrial.htm#ag.

enough nutrients to citrus crops without heavy fertilization (Furman et al., 1975). Like surrounding counties, the soils of Lake County are highly permeable and allow groundwater to percolate down quickly into the aquifer (Furman et al., 1975).

At the same time, according to the FLDOH database of potable well tests, the most common groundwater pollutants found in Lake County are total nitrate and nitrite (N+N), ethylene dibromide (EDB), and arsenic (see Figure 1). These pollutants have all been linked to the use of agricultural fertilizers, pesticides, herbicides, and/or soil fumigants (Chen, Ma, Hoogeweg, & Harris, 2001; Harrington, Maddox, & Hicks, 2010; Solo-Gabriele, Sakura-Lemessy, Townsend, Dubey, & Jambeck, 2003; US EPA, 2014a, 2014b), among other sources.

Sources of total N+N in groundwater include human wastewater and animal manure, but the use of fertilizers is the most prominent contributor (Harrington et al., 2010). When exposed to high levels of total N+N in drinking water, infants can suffer from blue baby syndrome, a blood disorder involving low oxygen levels, and that can be fatal (US EPA, 2014b). As a result the US EPA and the State of Florida set a health based standard, or maximum contaminant level (MCL), for total N+N in drinking water of 10,000 parts-per-billion (ppb).

Sources of arsenic in Lake County include runoff from agriculture, but also from electronics production and erosion of natural arsenic deposits. Ethylene dibromide (EDB) can enter groundwater through leaded gasoline spills and leaking storage tanks, as well as through wastewater from chemical production. However, EDB was also previously used as a pesticide (US EPA, 2014a), and among incidents of EDB contamination in Lake County, agricultural activities are often believed to be the source. Consuming water contaminated with high levels of EDB and arsenic, increases the risk of several adverse health outcomes, including cancer, skin damage, and problems with the circulatory, digestive, and reproductive systems (FLDOH, 2014;

US EPA, 2014a, 2014b). The current MCL for arsenic is 10 ppb, and the MCL for EDB set by the State of Florida is 0.02 ppb (which is stricter than the 0.05 ppb standard set by the US EPA).

EMPIRICAL MODEL

Several hedonic property value regression models are estimated, where the dependent variable is the natural log of the transaction price for home *i* in neighborhood *j*, when it was sold in period *t* (p_{ijt}). The hedonic price is estimated as a function of characteristics of the housing structure (e.g., age, interior square footage, number of bathrooms), the parcel (e.g., lot acreage) and its location (e.g., distance to urban centers and agricultural sites, being located on the waterfront), denoted by $\boldsymbol{x}_{ijt}$. The price of a home also depends on overall trends in the housing market, which are accounted for by annual and quarterly dummy variables $(\boldsymbol{M}_t)$. Of particular interest, we include measures of groundwater contamination in the potable well at home *i*, $f\left(test_{ijt}, \boldsymbol{ppb}_{ijt} | \boldsymbol{\theta}\right)$, which is a function of an indicator variable denoting whether the well water at home *i* was recently sampled and tested $\left(test_{ijt}\right)$ and the contaminant concentration results of those tests, which are measured in parts-per-billion $\left(\boldsymbol{ppb}_{ijt}\right)$. The equation to be estimated is:

$$\ln p_{ijt} = \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{M}_t\boldsymbol{\alpha} + f\left(test_{ijt}, \boldsymbol{ppb}_{ijt} | \boldsymbol{\theta}\right) + v_j + \varepsilon_{ijt} \tag{1}$$

where ε_{ijt} is a normally distributed error term. In some specifications we include block group level spatial fixed effects v_j to absorb all time invariant price effects associated with neighborhood *j*, and allow ε_{ijt} to be correlated within each block group *j*. The coefficients to be estimated are $\boldsymbol{\beta}$, $\boldsymbol{\alpha}$, v_j, and of particular interest $\boldsymbol{\theta}$.

A common criticism in hedonic applications is whether home sellers and buyers actually consider, or are even aware of, the environmental disamenity of interest and the measure assumed in the right-hand side of the hedonic price equation (Guignet, 2013). If not, then there is no reason to suspect that prices capitalize the disamenity. However, in the current context households are aware of groundwater pollution in their private well, at least in cases identified by FLDOH. In Florida sellers are required by law to disclose their drinking water source, and if it is a private well they must report the date of the last water test and the result of that test (Florida Association of Realtors, 2009). Additionally, when an issue is suspected FLDOH requests to test a homeowner's well in-person, and homeowners are then sent a letter notifying them of the test results. So in this context $test_{ijt}$ and $\boldsymbol{ppb}_{ijt}$ are directly observed by sellers, and likely buyers as well.

Previous studies found that regulatory standards for a contaminant may serve as a point of reference to households, and that property values respond to groundwater contamination levels relative to these standards (Boyle et al., 2010; Guignet, 2012). In our application, when the Florida Department of Health (FLDOH) sends a letter to homeowners, it categorizes contaminant test results by those that (i) exceed Florida's MCL or Health Advisory Levels (HAL), (ii) are above Florida's secondary drinking water standards, which reflect non-health "nuisance" based concerns, and (iii) that are above the detectable limit but below current standards. In our base models, we therefore model $f(\cdot)$ following a similar categorization scheme using a series of indicator variables:

$$
\begin{aligned}
& f\left(test_{ijt}, \boldsymbol{ppb}_{ijt} | \boldsymbol{\theta}\right) \\
& \qquad = test_{ijt}\theta_{test} + \theta_{DL}\mathbb{1}\left(\boldsymbol{ppb}_{ijt} > 0\right) + \theta_{MCL}\mathbb{1}\left(\boldsymbol{ppb}_{ijt} > \boldsymbol{MCL}\right) \qquad (2)
\end{aligned}
$$

where $\mathbb{1}\left(\boldsymbol{ppb}_{ijt} > 0\right)$ is an indicator variable equal to one if any contaminants were found above the detectable limit, and zero otherwise, and $\mathbb{1}\left(\boldsymbol{ppb}_{ijt} > \boldsymbol{MCL}\right)$ denotes whether any contaminants were at levels above the corresponding MCL (or HAL).[4] The variables $test_{ijt}$, $\mathbb{1}(\boldsymbol{ppb}_{ijt} > 0)$, and $\mathbb{1}(\boldsymbol{ppb}_{ijt} > \boldsymbol{MCL})$ are based on all tests taken Δt years before the transaction. The temporal window to consider in defining Δt is discussed in the next sections.

Under this functional form θ_{test} captures the price differential corresponding to homes that were recently tested for contamination (i.e., within Δt years before the transaction). The coefficient θ_{DL} captures the additional price differential among homes where at least one contaminant was recently found (relative to homes that were tested and no contaminants were found to be above the detectable limit). θ_{MCL} captures the additional change in price corresponding to homes where the recent test revealed at least one contaminant at levels above the corresponding MCL/HAL (relative to homes where contamination was found but all contaminants were below the MCL/HALs).

Since the coefficients of interest correspond to binary variables, following Halvorsen and Palmquist (1980) we calculate the percent change in price as:

$$\%\Delta p_{test} = \left(e^{\theta_{test}} - 1\right) \times 100 \tag{3}$$

$$\%\Delta p_{DL} = \left(e^{\theta_{test}+\theta_{DL}} - 1\right) \times 100 \tag{4}$$

$$\%\Delta p_{MCL} = \left(e^{\theta_{test}+\theta_{DL}+\theta_{MCL}} - 1\right) \times 100 \tag{5}$$

As discussed later in the Data section, the hedonic analysis focuses on all homes that were previously tested at any point before the sale. Therefore, $\%\Delta p_{test}$ is the percent change in price to homes that were recently tested but where no contamination was found, relative to homes that were tested in the more distant past, all else constant. Similarly, $\%\Delta p_{DL}$ and $\%\Delta p_{MCL}$ are the percent changes in price due to contamination levels for at least one contaminant being above the

[4] We do not account for secondary standards because not all contaminants have secondary standards, and there were few observations where concentrations exceeded the secondary standard but were less than the MCL/HAL.

detectable limit or the MCL/HAL, respectively, relative to homes that were not recently tested for groundwater contamination. Among this counterfactual group of homes, we presume that tests were no longer warranted because groundwater contamination was no longer a concern. The FLDOH will continue testing until the situation is resolved (e.g., contamination levels remain below the MCL/HAL for an extended period of time, or a permanent clean water supply is provided).

We could also change the counterfactual for the price comparison, for example the property value impacts from contamination above the detectable limit, relative to homes that were also recently tested but where no contamination was found is:

$$\%\Delta p_{test \rightarrow DL} = \left(e^{\theta_{DL}} - 1\right) \times 100 \quad (6)$$

Equations 1 through 6 are estimated for several variants of the hedonic regression, including specifications that do and do not include spatial fixed effects, and that do not distinguish between contamination levels above the detectable limit and MCL/HAL.

As with most hedonic applications, there is concern that there may be spatially dependent unobserved influences that affect property values. For example, a given neighborhood is usually built within a particular time period with several set home configurations, using similar building materials, and where the housing bundles are defined by similar local amenities and disamenities. Additionally, for the purpose of obtaining a mortgage loan, the comparable sales method is typically employed, which values a home using adjustments to several recent, nearby home sales. Failure to control for spatial dependence can potentially result in biased or inconsistent estimates.

To test for spatial dependence, we use the robust Lagrange Multiplier (LM) test of both the spatial error and lag format (LeSage & Pace, 2009). The spatial lag model includes a spatial lag of the dependent variable, of the form:

$$\ln p_{ijt} = \rho w p_{[ijt]} + \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{M}_t\boldsymbol{\alpha} + f\left(test_{ijt}, \boldsymbol{ppb}_{ijt}|\boldsymbol{\theta}\right) + v_j + \varepsilon_{ijt} \quad (7)$$

where ρ is a spatial lag parameter to be estimated and $wp_{[ijt]}$ is the corresponding element from the n×1 vector obtained after multiplying the spatial weights matrix (SWM) $\boldsymbol{W}$ and the price vector $\boldsymbol{P}$. In other words, $wp_{[ijt]}$ is the spatially and temporally weighted average of neighboring prices allowed to influence the price of home *i*, sold in period *t*. The spatial error model (SEM) instead models unobserved spatial dependence in the error term, as:

$$\ln p_{ijt} = \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{M}_t\boldsymbol{\alpha} + f\left(test_{ijt}, \boldsymbol{ppb}_{ijt}|\boldsymbol{\theta}\right) + v_j + \varepsilon_{ijt}, \text{ where } \varepsilon_{ijt} = \lambda w \varepsilon_{[ijt]} + u_{ijt} \quad (8)$$

Here, λ is the spatial autocorrelation parameter to be estimated, $w\varepsilon_{[ijt]}$ is the corresponding element from the n×1 vector obtained after multiplying the SWM $\boldsymbol{W}$ and vector of error terms $\boldsymbol{\varepsilon}$, and $u_{ijt} \sim N(0, \sigma^2)$.[5]

Robust versions of the spatial lag and error LM tests were used to test for spatial dependence and choose between the lag and error models. In all cases the null hypothesis of no spatial dependence was rejected and in each format the spatial error model (SEM) had significantly larger LM test coefficients, supporting the SEM over the lag format. Due to concerns with simultaneous lag and error dependence, we also estimated the general spatial model for all model variations (LeSage & Pace, 2009), which includes both a spatial lag of the dependent variable and

[5] A variety of spatial weights matrices (SWMs) were explored. In spatial econometrics, SWMs are used to exogenously specify the spatial relationships between "neighboring" home sales. We favor SWMs that identify neighbors based on distance and time, so that nearby and more recent home sales are given nonzero weights. We use alternative time constraints of 6 months, 12 months, and 18 months prior to a transaction, and include 3 months after to account for delays between contract and sale. The spatial radii used to identify neighbors are 800, 1,600, and 3,200 meters. The inverse distance between the two homes is used as the individual entry in the SWM, which is row-standardized so that the weights corresponding to each transaction sum to one (LeSage and Pace, 2009).

a spatially correlated error term. In all cases, the spatial lag parameter ρ was insignificant, while the spatial error parameter λ was significant at the 99% level. Together, these series of tests clearly demonstrate that the SEM best reflects the spatial nature of the underlying data generating process.[6]

DATA

The hedonic analysis focuses on transactions of single-family homes from 1990 to 2013 in Lake County, Florida, just west of Orlando. The main components of the data are described below.

Groundwater Well Test Samples

The Florida Department of Health (FLDOH) regularly tests groundwater wells for contamination and maintains a database of all wells identified and assessed, along with the test results, from 1982 to present for the entire State. Our focus is on private potable wells, but the dataset also includes publically owned wells and some irrigation and abandoned wells.

The FLDOH conducts these tests for a slew of different reasons, but in most cases a sister agency, usually the Florida Department of Environmental Protection (FLDEP), notifies the FLDOH of a potential contamination issue caused by human activity.[7] The FLDOH then surveys

[6] Following LeSage and Pace (2009), we selected the SWM with the highest log-likelihood in the majority of models, which turned out to be the one with a distance radius of 3,200 meters and a temporal window of 12 months. Across the different SWMs, however, differences were miniscule.

[7] FLDOH's groundwater testing program focuses on contamination issues caused by human activities, and generally does not investigate groundwater contamination due to natural causes, although some issues are later determined to be from natural causes.

the potentially impacted area (usually a ¼ mile radius around the area of concern). Several wells (about 10 or so) within the potentially impacted area are first tested. If contamination is found, additional wells are tested and the well survey area is iteratively expanded as needed to fully assess any potential contamination issues. In some cases, FLDOH and FLDEP may first become aware of potential contamination because residents complain that their water smells or tastes odd.

The FLDOH can only carry out a well test if it receives consent from the property owner. Although the vast majority agrees to have their well tested, occasionally homeowners do refuse.[8] In any case, it is clear that the groundwater test data used in this study is not random, and should not be interpreted as a representative sample of the groundwater quality in Florida. Nonetheless, these data are useful in identifying how property values respond to contamination in private potable wells, at least among properties where testing has occurred.

In the time between 1982 and 2013 there is a record of 71,365 private potable groundwater wells in Florida that were identified and assessed by FLDOH. We carefully matched groundwater tests at these private potable wells to the corresponding residential parcels and transactions. The matching procedure relies on both an address matching algorithm, which links wells and parcels based on similar address fields, as well as spatial matching, which exploits the spatial relationship between well coordinates and parcel boundaries. Both techniques are used in conjunction to accurately link residential parcels to the corresponding groundwater well tests and contamination levels at the time of sale.[9]

[8] Of the 6,619 private drinking water wells in Lake County that were identified by the FLDOH, test results were not available for 365 (5.5%) wells. These wells may not have been tested because the well owner refused FLDOH's request. That said, these non-tested wells could also belong to homes with multiple wells but where only one well was tested.

[9] See the Appendix for details.

We focus on the 6,619 private potable wells that were matched to a home in Lake County. To test a well suspected to be supplying polluted drinking water, the FLDOH first retrieves a water sample from the well and examines the sample for detectable concentrations of specific contaminants. Households are then sent the actual lab test results, along with a letter explaining how to interpret the results and explicitly categorizing any contaminants found as having levels: (i) above Florida's Maximum Contaminant Level (MCL) or Health Advisory Levels (HAL), (ii) above Florida's secondary drinking water standards, which reflect non-health "nuisance" based concerns, or (iii) above the detectable limit but below current standards.

If contamination is found to be present in the sample, and at concentrations above the MCL/HAL, households are advised not to consume the well water. If needed, actions are often taken to reduce pollutant concentrations in a household's water, including drilling a new well, installing a filter, and if possible providing a connection to the public water line (FLDOH, 2014). All costs are covered by FLDEP's Water Supply Restoration Program, and the FLDOH will usually continue to test the groundwater until contamination levels are below the MCL (or State HAL) and believed to be safe, or if a permanent clean water supply is provided.

The FLDOH records 6,652 total water samples taken in Lake County, with the earliest in 1983 and the most recent in 2013. Since the number of samples is greater than the number of observed wells, it is clear that some wells were indeed sampled multiple times. As shown in Figure 1, total N+N, EDB, and arsenic are the three most common contaminants in Lake County.

Lake County Parcels and Transactions

In Lake County 74,422 residential parcels were sold at least once during the 1990 to 2013 study period.[10] Of these parcels, 3,416 were identified by FLDOH as having at least one private potable well; test results were available for 3,288 of these parcels. Among those, 2,110 residential parcels were found to have at least one contaminant at levels above the detectable limit, including 158 parcels with at least one contaminant above the corresponding MCL/HAL.

There were a total of 124,859 arms-length transactions of single-family homes from 1990-2013.[11] Of these unique sales, 5,738 were of parcels with a tested well. Only in 1,730 of these cases, however, did a test take place prior to the sale. With this final dataset of n=1,730 residential transactions where we have data on actual contamination levels at (or prior to) the time of the sale, we examine how residential property prices respond to groundwater contamination.

Table 1 shows that 1,135 of these transactions had tests that revealed contaminants at concentrations above the detectable limit (*above DL*), and 180 of those transactions had at least one contaminant at concentrations above the corresponding MCL or HAL (which we denote simply as *above MCL*). The number of identifying observations decreases as we consider smaller temporal windows before the date of transaction (Δt = 1, 2, or 3 years). The temporal window is something we investigate in the Results section, but the main hedonic analysis focuses on groundwater pollution found within $\Delta t = 3$ years prior to a transaction. Considering the three most

[10] Data on residential parcels, characteristics, and transactions were obtained from the Lake County Property Appraiser's Office.

[11] Homes recorded as having more than twelve bathrooms or greater than 50 acre plots were omitted. We also eliminated homes where the real price (2013$) was in the top or bottom 1% percentiles.

common contaminants, descriptive statistics of the maximum concentrations found at a home within three years prior to the sale date are shown in Table 2.

In order to cleanly identify property value impacts we must control for other characteristics of a housing bundle that may influence price. We include home structure characteristics such as the age and quality of the home, number of bathrooms, interior square footage, land area of the parcel, and whether the house has a pool and air conditioning. Recognizing that the location of the house in relation to amenities and disseminates also greatly explains variation in home values, we include several location characteristics, such as: the number of gas stations within 500 meters; distances to the nearest primary road, golf course, and protected open space; and whether the home is a lakefront property or located in a floodplain. To control for confounding factors associated with proximity to likely pollution sources, we use GIS data from the Florida Fish and Wildlife Conservation Commission (FFWCC), and include the inverse distance to different agricultural lands, namely distance to the to the nearest citrus grove and row crops.[12] We also account for a

[12] These variables were derived using GIS data from the following sources. Data of golf courses and lakes and ponds were obtained from the Lake County Government website, (http://www.lakecountyfl.gov/departments/information_technology/geographic_information_services/datadownloads.aspx, accessed March 3, 2015). Citrus groves and row crop data were obtained from the FFWCC (http://ocean.floridamarine.org/TRGIS/Description_Layers_terrestrial.htm#ag, accessed Feb. 6, 2015). Primary roads were identified based on the US Census Bureau's 2010 TIGER/Line files (http://www.census.gov/geo/maps-data/data/tiger-line.html, accessed Sept. 16, 2013). GIS data of gas stations were identified from NAVTEQ's 2009 and 2012 "Auto_Svc" data (Facility type = 5540). Data of protected open space were obtained from USGS's 2012 GAP analysis (http://gapanalysis.usgs.gov/padus/data/download/, accessed Sept. 16, 2013), and floodplain data were from FEMA's 2012 National Flood Hazard Layer.

home being located within the existing public water system service area.[13] Descriptive statistics of the housing structure and spatial characteristics are displayed in Table 3.

RESULTS

The hedonic regressions were estimated using all n=1,730 transactions from 1990 to 2013, where data on potable well contamination prior to the sale were available. Admittedly this is a fairly long time period to be imposing a single hedonic surface, and thus a constant equilibrium, but given the small sample size we view this as an acceptable tradeoff. All regressions include year and quarter dummy variables to account for overall housing market trends.

Property Value Impacts of Groundwater Contamination

The base model hedonic results in Table 4 focus on well water tests and contamination results within 3 years prior to the sale. All the variables in Table 3 are included in the hedonic regressions, but only the estimates of interest are shown.[14] The coefficient estimates not displayed all showed the expected sign or were insignificant. The adjusted R-squares ranged from 0.770 to

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[13] In parts of Florida households within the public water service area may not necessarily be connected to public water and may still use private wells as their potable water source. Public water service area data obtained from the St. Johns River Water Management District (http://www.sjrwmd.com/gisdevelopment/docs/themes.html, accessed on March 26, 2015).

[14] The only exception is that distance to the nearest major road was excluded due to multicollinearity concerns; the estimates of interest, however, are robust to this exclusion. Lot size and interior square footage entered in log-form, and the inverse distance to the nearest citrus grove, row crop, and golf course were used instead of linear distance. Companion missing dummy variables were included to account for missing values of lot size, bathrooms, and age of home.

0.801, indicating fairly good overall statistical fits. In the OLS model (model 1.A) we see that testing for contamination within the last three years (*tested*) is negatively correlated with home prices, and that finding contamination levels above zero or, more precisely, above the detectable limit (*above DL*) leads to an additional decrease in prices. Both coefficients, however, are small (-0.0239 and -0.0146, respectively) and are not statistically different from zero.

The second panel shows the estimated percent changes in price, as calculated in equations (3) through (6). Although testing ($\%\Delta p_{test}$) and (conditional on testing) finding contamination ($\%\Delta p_{test \rightarrow DL}$), when considered separately, have insignificant effects on home prices, together there does seem to be a significant impact, as suggested by $\%\Delta p_{DL}$. Testing *and* finding contamination within the last three years suggests a 3.77% decline in home value, according to model 1.A. Similar results are found in model 1.B, which includes block group fixed effects to account for all time invariant price effects associated with a particular neighborhood. In both models, the only significant price impact corresponds to $\%\Delta p_{DL}$, suggesting a 2.52 – 3.77% depreciation. Multiplying $\%\Delta p_{DL}$ by the mean price of a non-tested home ($171,563) suggests an average loss of $4,322 – $6,475. This depreciation is relative to homes where groundwater contamination was previously suspected and/or confirmed, but where any past issues have since been resolved (since the FLDOH no longer deemed it necessary to continue to monitor the well).

Finally, a spatial econometric model is estimated to better control for the spatial nature of the underlying data generating process. Model 1.C is a spatial error model (SEM) (LeSage & Pace, 2009) that uses a SWM with distance and time constraints of 3,200 feet and 12 months. The spatial coefficients are comparable to the OLS results, with minor differences in magnitude. The significant spatial autocorrelation coefficient λ demonstrates that the error terms are spatially correlated. The combined impact of testing and a result above the detectable limit is a negative

3.63% in this model, which reflects a mean loss in value of $6,228 and is significant at the 99% level.

Models 1.D, 1.E, and 1.F are the same as the previous three models, but include an additional interaction term to investigate whether contamination levels above the MCL or HAL lead to an additional decrease in value.[15] We find no statistically significant impacts from contamination levels above the MCL/HAL. This is not necessarily surprising since mitigating and averting actions can be taken, and are often performed by FLDEP at no cost to the homeowner when the MCL/HAL is exceeded (FLDEP, 2014). That said, this result could also be partially due to the small number of transactions where the MCL/HAL was exceeded (n=48, see Table 1). Across all three models we see that $\%\Delta p_{DL}$ equals a 2.65% to 3.77% depreciation, again suggesting that recent testing and detection of private well contamination leads to a small but significant decrease in home values. Since the SEM estimates fall within those of the OLS and fixed effect (FE) models, and are fairly close to the OLS results, we focus on OLS and FE models for the remainder of the analysis.

Property Value Impacts Over Time

We next investigate whether the property value impacts from groundwater testing and contamination are permanent or diminish over time. Variants of models 1.A and 1.B are re-estimated but now separately account for homes with private wells that were tested within one year prior to the transaction, 1 to 2 years, 2 to 3 years, and so on, out to 7 to 8 years prior. In accounting

[15] Note that our notation commonly refers to the regulatory standard as *MCL*, but we use this notation to refer to both EPA's MCL and Florida's more stringent HAL, when applicable.

for tests and test results in one year increments we examine how $\%\Delta p_{DL}$ varies overtime. The $\%\Delta p_{DL}$ estimates are calculated following equation 4 and graphed in Figure 2.

The OLS and FE models suggest that home values are 5.94% and 3.75% lower, respectively, when the private well was tested and contamination found within one year before the transaction. The OLS model also suggests a significant 5.81% decline corresponding to testing and contamination within 2 to 3 years prior to the transaction. Otherwise the price impacts are statistically insignificant. The point estimates gradually tend towards zero, and the 95% confidence intervals widen, when considering well water testing and contamination that was found more than 3 years earlier.

The FLDOH generally continues to test a private well until contaminants are found to be at levels below the MCL/HAL for an extended period of time, or in some cases once a permanent clean water supply can be provided (e.g., connecting to the public water system). Although the results suggest that testing and contamination in a private drinking water well lead to an initial 3% to 6% decline in home value, this decrease is not permanent and seems to diminish a few years after the situation is resolved.

Heterogeneity Across Contaminants

In order to examine whether the property value impacts vary across different contaminants, variants of the base model regressions from Table 4 were re-estimated with a series of interaction terms to allow the price effects of the most common pollutants (total nitrate and nitrite (N+N), ethylene dibromide (EDB), and arsenic) to vary from other contaminants in general. The results are omitted for brevity, but in short we find no statistically significant difference in the price impacts from total N+N, EDB, or arsenic, compared to contamination in general. This finding must be interpreted with caution, however, because as shown in Table 2 the number of transactions available for statistical identification gets very small when focusing on individual contaminants (with the exception of total N+N).

Price and Concentration of Total Nitrate and Nitrite

There is a fairly large number of transactions where detectable levels of total N+N were found within three years before the sale date (see table 2), allowing for an explicit examination of how price impacts vary with increasing levels of total N+N in private groundwater wells. Variants of models 1.A and 1.B from table 4 are re-estimated to include the maximum concentration of total N+N found within three years before the transaction, measured in parts-per-billion $\left(ppb_{ijt}^{NN}\right)$.

Different functional forms of the relationship between $\ln p_{ijt}$ and ppb_{ijt}^{NN} are assessed, including linear and piecewise-linear models. The estimated coefficients are used to calculate the corresponding percent change in price $\left(\%\Delta p_{ijt}^{NN}\right)$ as a function of parts-per-billion (ppb) of total N+N. The linear specification provided no robust evidence of a significant relationship between prices and concentrations of total N+N, and so the results are omitted.

To examine whether the 10,000 ppb health based standard is serving as a point of reference for home buyers and sellers, we estimate a piecewise-linear model where the slope coefficients at concentrations below and above the MCL are allowed to differ. The percent change in price is estimated as:

$$\%\Delta p_{ijt}^{NN} = \left(e^{\left\{\theta_{test}+\theta_{DL}+(\theta_{NN}\times ppb_{ijt})+\left(\theta_{NN\_MCL}\times\left(ppb_{ijt}^{NN}-MCL\right)\times\mathbb{1}\left(ppb_{ijt}^{NN}>MCL\right)\right)\right\}}-1\right)\times 100 \qquad (9)$$

where the parameters to be estimated include: θ_{NN}, which denotes the slope coefficient corresponding to the concentration of total N+N $\left(ppb_{ijt}^{NN}\right)$, and θ_{NN_MCL}, which captures the change in the slope once the 10,000 ppb MCL is exceeded. This exceedance is denoted by the dummy variable $\mathbb{1}\left(ppb_{ijt}^{NN} > MCL\right)$. Figure 3 shows that the price effects are insignificant at total N+N levels below the MCL, but once exceeded there is a statistically significant decline in home values, which continues as total N+N concentrations increase. In fact, at levels twice the MCL the average loss in value is as much as $11,893 to $25,845.

CONCLUSION

There are only a few rigorous hedonic studies examining how home values are directly impacted by changes in groundwater quality (Boyle et al., 2010, Guignet, 2013). We attribute this gap in the literature largely to the lack of appropriate data and difficulties in linking groundwater quality measures to individual homes and transactions. In this paper we used a comprehensive dataset of groundwater contamination tests of potable wells, conducted by the Florida Department of Health (FLDOH). We implemented a dual matching procedure that utilized property and groundwater well address fields, along with spatial coordinates and parcel boundaries, to establish accurate matches and ultimately link residential transactions to groundwater tests and contaminant levels relative to the date of sale. This allowed us to investigate how home-specific levels of groundwater contamination in private potable wells impact property values, thus providing some insight for benefit-cost analyses of policies to improve and protect groundwater quality.

Contamination of nutrients and other chemicals linked to agricultural fertilizers and pesticides are increasingly impacting surface and groundwater quality.[16] Our hedonic study

[16] In EPA's 2000 National Water Quality Inventory, states reported that agricultural nonpoint source pollution was the leading source of water quality impacts on surveyed rivers and lakes, the second largest source of impairments to wetlands, and a major contributor to contamination of surveyed estuaries and ground water.

focused on Lake County, Florida, where a large component of groundwater pollution concerns stem from runoff of chemicals associated with orange groves and other agricultural activities. The most frequently detected contaminants observed in the data were total nitrate and nitrite (N+N), ethylene dibromide (EDB), and arsenic, all of which have been linked to agricultural fertilizers, pesticides, herbicides, or soil fumigants (Chen et al., 2001; Harrington et al., 2010; Solo-Gabriele et al., 2003; US EPA, 2014b). Human exposure to these contaminants can increase the risks of numerous adverse health outcomes, including infant mortality, blue-baby syndrome, cancer, and issues with the liver, stomach, and circulatory and reproductive systems (US EPA, 2014b).

Our hedonic results suggest that groundwater pollution in a private potable well does impact the value of a home, generally leading to a 2% to 6% depreciation. This price impact is not permanent, however, and seems to diminish a few years after the contamination issue is resolved. In their study of naturally occurring arsenic contamination in Maine, Boyle et al. (2010) also found that prices rebound a few years after contamination.

Focusing on individual contaminants (total N+N, EDB, and aresenic) we found no significant heterogeneity in how the housing market responds. Although this conclusion is confounded by the fact that very few identifying transactions were available when focusing on individual contaminants. A valuable direction for future research is to further examine whether different contaminants affect home values differently. If the price impacts are in fact similar across different contaminants, and perhaps even sources, then this would facilitate benefit transfer to other groundwater contamination contexts, such as leaking underground storage tanks, hydraulic fracturing and natural gas extraction, and hazardous chemicals from superfund sites.

Focusing on total N+N we explicitly modelled how home values are impacted at different concentration levels, and found that relatively low concentrations have an insignificant impact on residential property prices. In contrast, once the health based regulatory standard, or maximum contaminant level (MCL), is exceeded, home values decline sharply. In fact, home values decrease by 7% to 15% at contamination levels twice the MCL (corresponding to an average loss of $11,893 to $25,845). This finding is in-line with past risk communication and valuation research (Boyle et al., 2010; Guignet, 2012; Johnson & Chess, 2003; Smith, Desvousges, Johnson, & Fisher, 1990), supporting the notion that given little knowledge of how pollution maps into health risks, households use the regulatory standard as a point of reference in forming their perceived risks. Along this vein, this finding also supports our overall analysis by demonstrating that households are responding to the information provided by regulators.

FIGURES AND TABLES

Figure 1: Most Frequent Groundwater Contaminants Detected in Lake County, FL.

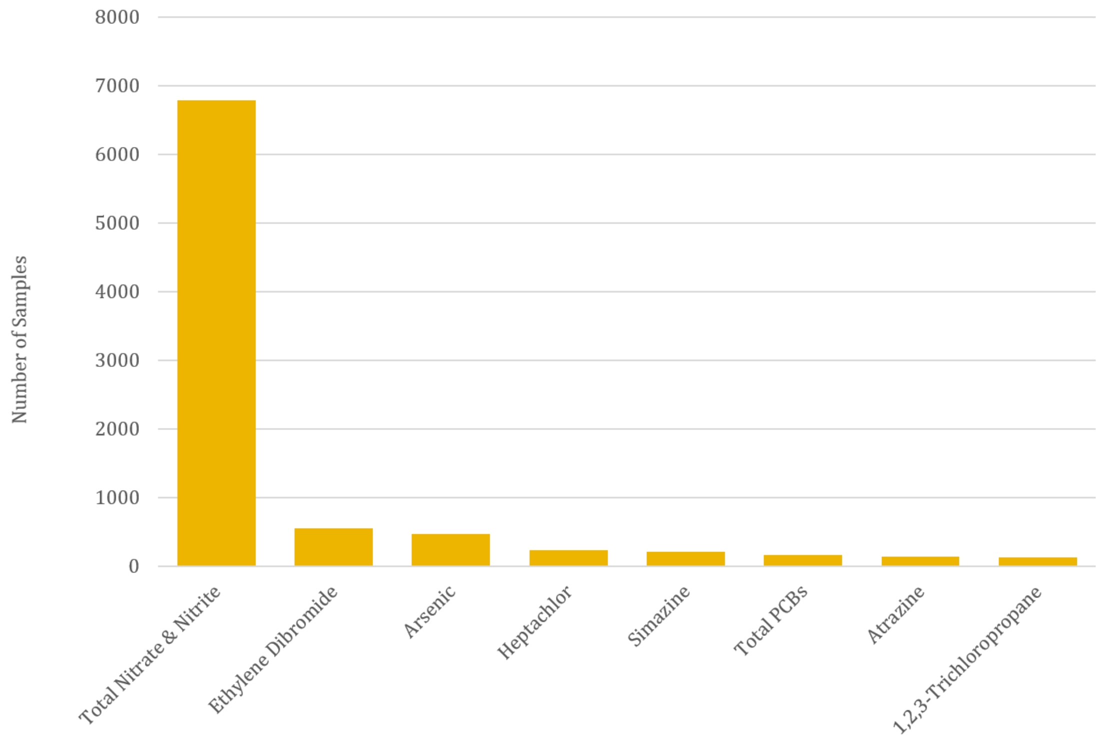
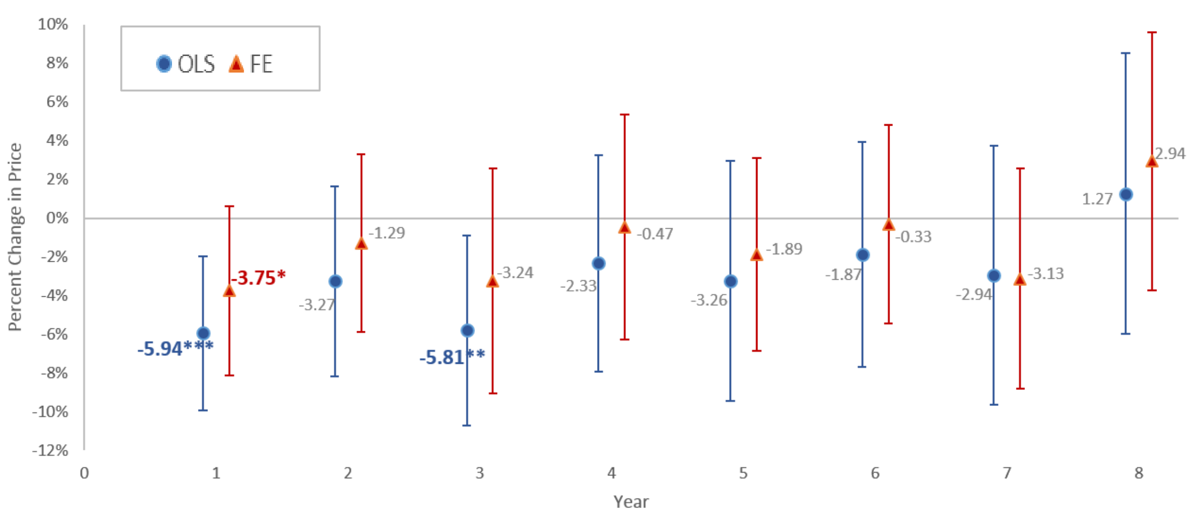
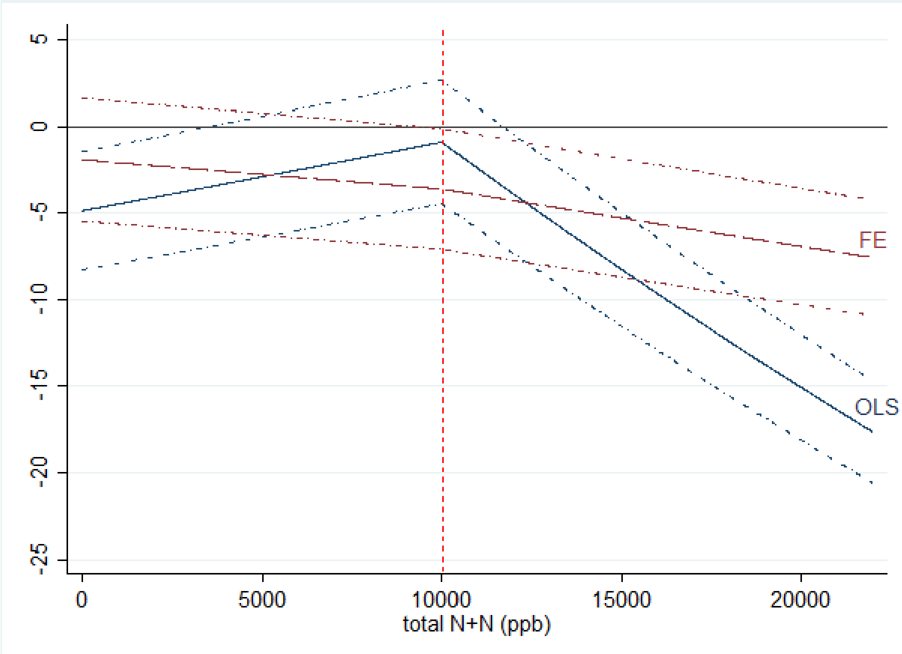


Figure 2: Price Impacts of Testing and Contamination Over Time.



*** p<0.01, ** p<0.05, * p<0.1. Estimates of $\%\Delta p_{DL}$ from OLS (denoted by circles) and fixed effect (FE) models (denoted by triangles). Vertical lines represent the 95% confidence intervals.

Figure 3: Percent Change in Price and Concentration of Total Nitrate and Nitrite: Piecewise-linear Specification.



Concentration of total nitrate and nitrite (measured in parts-per-billion) displayed on x-axis, and percent change in price displayed on y-axis (see equation 10). Solid line denotes the OLS model and long dashed line denotes the census block group fixed effect (FE) model. Dotted lines denote the 95% confidence intervals (derived using the "predictnl" command in Stata 13).

Table 1: Number of Sales where Private Well Tested: By Time Prior to Sale and Test Results.

Variable	Time Before Sale Date 1 Year	2 Years	3 Years	Any Time Before Sale Date
Tested	413	615	793	1,730
Above Detectable Limit	287	411	524	1,135
Above Maximum Contaminant Level	24	38	48	180

Table 2: Summary Statistics of Pollutant Concentrations Above Detectable Limit: Tests 3 Years Prior to Sale.

Contaminant	Observations	Average ppb	Min. ppb	Max. ppb	MCL/HAL ppb
Total Nitrate + Nitrite (N+N)	477	3,746.187	15	22,000	10,000
Ethylene Dibromide (EDB)	20	0.0701	0.0027	0.46	0.02
Arsenic	22	4.0706	0.1160	23.6	10

Table 3: Descriptive Statistics for Home and Location Characteristics (n=1,730 sales).

Variable[a]	Obs	Mean	Std. Dev.	Min.	Max.
Price of home (2013$ USD)	1,730	215,977.2	107,667.1	20,000	525,000
Age of home (years)	1,701	12.5332	15.3015	0	123
Number of bathrooms	1,730	2.2017	0.6923	1	7
Interior square footage	1,730	2,031.902	779.7661	396	6,558
Lot size (acres)	956	2.1009	2.4005	0.1251	15.16
Quality of construction[b]	1,730	583.4942	79.0632	100	710
Air conditioning	1,730	0.9751	0.1557	0	1
Pool	1,730	0.3260	0.4689	0	1
Distance to urban cluster (km)	1,730	17.3645	5.9100	0.2083	27.8515
In 100-year flood plain	1,730	0.0688	0.2532	0	1
Number of gas stations within 500 meters	1,730	0.0491	0.2241	0	2
Waterfront home	1,730	0.1156	0.3198	0	1
Distance to nearest protected area	1,730	1,873.717	1,504.043	12.7204	6,553.036
Distance to nearest primary road	1,730	1,1176.95	6,414.878	149.7474	24,139.85
Distance to nearest lake or pond	1,730	340.1355	270.5953	0	2,132.23
Distance to nearest citrus grove	1,730	364.5416	385.4437	0	5,815.711
Distance to nearest row/field crop	1,730	249.673	240.5691	0	1,735.105
Distance to nearest golf course	1,730	2,644.59	2,786.067	19.3349	17,722.05
In public water system service area	1,730	0.1844	0.3879	0	1

a. All characteristics are dummy variables unless otherwise noted. Distance variables measured in meters unless otherwise noted.
b. Construction quality based on County Assessor gradings where 50 = poorest quality and 950 = best quality.

Table 4: Base Hedonic Regression Results: Tested 3 Years Prior to Sale.

VARIABLES	OLS (1.A)	FE (1.B)	SEM (1.C)	OLS (1.D)	FE (1.E)	SEM (1.F)
Tested	-0.0239	0.0021	-0.0220	-0.0239	0.0020	-0.0220
	(0.019)	(0.019)	(0.0172)	(0.019)	(0.019)	(0.0172)
× Above DL	-0.0146	-0.0276	-0.0150	-0.0145	-0.0288	-0.0150
	(0.018)	(0.017)	(0.0182)	(0.018)	(0.018)	(0.0185)
× Above MCL				-0.0007	0.0153	-0.0004
				(0.040)	(0.038)	(0.0367)
lambda (λ)			0.1040***			0.1040***
			(0.0145)			(0.0145)
$\%\Delta p_{test}$	-2.36	0.21	-2.17	-2.36	0.20	-2.17
	(1.84)	(1.89)	(1.68)	(1.84)	(1.89)	1.68
$\%\Delta p_{test\rightarrow DL}$	-1.45	-2.73	-1.49	-1.44	-2.84*	-1.49
	(1.79)	(1.68)	(1.79)	(1.78)	(1.72)	(1.82)
$\%\Delta p_{DL}$	-3.77***	-2.52**	-3.63***	-3.77***	-2.65**	-3.63***
	(1.32)	(1.23)	1.31	(1.35)	(1.33)	1.35
$\%\Delta p_{MCL}$				-0.07	1.55	-3.66
				(4.00)	(3.85)	3.47
Observations	1,730	1,730	1,730	1,730	1,730	1,730
Block Group FE	No	Yes	No	No	Yes	No
# of FE's	-	65	-	-	65	-
R-squared	0.798	0.770	0.800	0.798	0.770	0.801

Note: Dependent variable is the natural log of the real transaction price (2013$ USD). Only coefficients of interest are shown, including *Tested* and interaction terms capturing the incremental impact of contamination levels above the detectable limit (*Tested* × *Above DL*) and above the MCL (*Tested* × *Above MCL*). Robust standard errors appear in parentheses below estimates. In spatial fixed effects (FE) models, standard errors are clustered at the fixed effect level. Models 1.C and 1.F are spatial error models (SEMs) where the error terms are allowed to be spatially correlated based on inverse distance SWMs. Models 1.C and 1.F use a SWM with a distance radius of 3,200 feet, and a time constraint of 12 months (see the Empirical Model section for details).
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX. PRIVATE WELL AND RESIDENTIAL PARCEL MATCHING.

In order to link private potable wells to residential parcels a dual address and spatial matching procedure was implemented, where matches were based on a common address field and the spatial relationship of the well relative to the parcel boundaries.[17] Both techniques are used in conjunction to accurately link residential parcels to the corresponding groundwater well tests and contamination levels at the time of sale.

Both the parcel and well datasets had text fields denoting the corresponding street address. Although clean matches could be determined between the street number, zip code, and city name, the street name sometimes proved problematic. The street names were not always entered in a consistent manner within or across datasets. These fields were standardized to the best of our ability based on United States Postal Service standards (USPS, 2013), but there were still inconsistencies and potential spelling errors, implying that matching based only on exactly equivalent text strings would disregard some valid matches.

Therefore an index was developed based on the "Levenshtein edit distance", a metric denoting the number of single character substitutions, insertions, or deletions that would be necessary to convert one text string into another.[18] This metric was normalized by dividing by the number of characters in the longer of the two address fields, yielding a zero to one index where zero denotes a perfect match and one implies no match. This allowed us to assess the similarity between the street name fields listed for each well and parcel.

As shown in Table A.1, the majority of the matches are perfect matches, where the address fields are exactly the same (the city and/or zip code are the same, the street numbers are equal, and

[17] We thank Abt Associates for developing and programming much of the well-parcel matching procedure.
[18] This metric was calculated using a Stata module available at: https://ideas.repec.org/c/boc/bocode/s457547.html, accessed December 9, 2014.

the street name match quality index = 0). Visual inspection confirmed, however, that some addresses that were clearly the same were not being picked up by this criteria alone. We therefore allowed for approximate matches based on near identical address fields (the city and/or zip code are the same, street numbers are equal, and match quality index ≤ 0.10). Visual inspection of the data confirmed that this was an appropriate, but conservative, threshold, as to not falsely match a well to a parcel. Nonetheless, some accurate well-parcel matches were still not being identified.

Table A.1: Classification of Well-to-Parcel Matches and Sales Tested Before Sale Date

Match Classification	Parcels	Sales
Perfect Match	5,682	1,463
Approximate Match	441	116
Weak Approximate Match w/ Location Match	491	137
Location Match w/ Same Street Number	77	14
Total Matched	6,691	1,730

Using Geographic Information Systems (GIS) we established potential location based matches based on whether the well coordinates fell within the boundaries of a particular residential parcel. Although computationally easy, the location based matching by itself unfortunately proved inaccurate, likely due to the somewhat coarse accuracy of hand-held GPS units and GIS data (a few meters margin of error), and the fact that well-heads tend to be located near parcel boundaries. Nonetheless, the locational information was used to supplement the address matching procedure.

Weak approximate matches with a location match were identified as those where the city and/or zip code were the same, street numbers were equal, street name match quality index ≤ 0.50 (but > 0.10), and where the well coordinates were within the parcel boundary. Lastly, since the zip code and city fields were sometimes missing within one or both datasets, we also allowed matches where the street numbers were the same, match quality index ≤ 0.50, and where the well coordinates were within the parcel boundary, but the city and/or zip code did not need to be equivalent.

Short of manually going through all possible well and parcel combinations, we believe this procedure yields a comprehensive and accurate set of unique well-parcel matches (n=6,691). In the main hedonic analysis, the property value regressions are estimated using the n=1,730 transactions where a home was matched to a private well, and where the well water was tested prior to the transaction. The results are robust, however, if we re-estimate the regressions using only the sample of n=1,463 sales with perfect matches.

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