

Impacts of Ground Water Contamination on Property Values: Agricultural Run-off and Private Wells

Dennis Guignet, Patrick J. Walsh, and Rachel Northcutt

Few studies have examined the impacts of ground water quality on residential property values. Using a unique data set of well tests, we link residential real estate transactions to home-specific contamination and conduct a hedonic analysis of sales in Lake County, Florida, where pollution concerns relate primarily to agricultural run-off. We find that recent testing and contamination of ground water there correspond to a 2–6 percent depreciation in home values, an effect that diminishes over time. Focusing on nitrogen-based contamination, we find that prices decline mainly when concentrations exceed the regulatory health standard, suggesting as much as a 15 percent depreciation at levels twice the standard.

Key Words: drinking water, ground water, hedonic, nitrate, nitrite, potable well, property value, water quality

Estimating the value of ground water resources and the services they provide is critical to formulating policies meant to protect and improve water quality. One of the most crucial services provided by ground water is that it is an important source of drinking water. In the United States, ground water is the source for 77 percent of community water systems, and about 15 percent of the population rely on private wells for water (Environmental Protection Agency (EPA) 2012a, 2012b). Private wells are particularly susceptible to potential contamination because they are not regulated under the Safe Drinking Water Act and are not required to undergo regular monitoring and treatment to ensure water quality standards are met. Furthermore, households that rely

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on private wells tend to be in rural areas where local aquifers are potentially vulnerable to contamination from nearby agricultural activities.

Hedonic property value methods are useful for estimating welfare impacts from changes in ground water quality. Private wells and the quality of the water in the local aquifer are inherently linked to the housing bundle—the collection of characteristics that contribute to the value of the property—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 impacts on property values reflect changes in the present value of the future stream of expected utility derived from the housing bundle. Given the number of household activities that depend on safe water, a contaminated well could 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 of ground water quality. We attribute this gap in the literature largely to a lack of appropriate data and difficulties associated with linking measures of ground water quality to individual homes. The results of well tests typically are not publicly available so most prior studies of ground water have used distance or spatially aggregated measures as proxies for contamination. We use a unique, comprehensive data set of ground water contamination tests conducted by the Florida Department of Health (FDH). We use the data set to link residential property transactions to home-specific levels of contamination in private potable wells and conduct a hedonic analysis to examine how property values respond to ground water pollution in Lake County, Florida, where a large proportion of such pollution stems from pesticide and fertilizer run-off from orange groves and other agricultural activities.

To our knowledge, this is the first hedonic study to link data on water quality in private potable wells to individual homes and to have a data set rich enough to examine the relationship between the concentration of pollution in ground water and residential property values. Furthermore, this is the most rigorous hedonic study to date to examine the impact of agriculture-related ground water pollution on residential property values.

Using a data set of residential transactions from 1990 through 2013, we empirically examine four primary questions. First, are home values systematically lower in the presence of ground water pollution? Second, if so, how does the price differential vary over time? Third, does the price differential vary with the type of contaminant? Finally, do home prices vary with the magnitude of pollutant concentration?

Literature Review

Since Rosen (1974) first established the underpinnings that connect hedonics to welfare analysis, there has been a flurry of hedonic studies of the relationship between property values and a variety of environmental

amenities and disamenities.¹ Studies of the link between water quality and property prices date back to the 1960s (David 1968), but water quality monitoring has only recently begun to be comprehensive enough to facilitate widespread analysis. Since 2000, federal, state, and local monitoring efforts have increased significantly and expanded the amount of available data.

Several earlier studies found a significant relationship between water quality and property values (Michael, Boyle, and Bouchard 2000, Poor et al. 2001, Gibbs, Halstead, and Boyle 2002). Many of the studies from that time used available data on water clarity in northeastern U.S. lakes. Recent studies have expanded the types of waterbodies analyzed (Artell 2013, Netusil, Kincaid, and Chang 2014), the water quality parameters used (Bin and Czajkowski 2013, Walsh and Milon 2015), and the populations affected (Poor, Pessagno, and Paul 2007, Walsh, Milon, and Scrogin 2011) but have focused almost exclusively on surface water. Surface waters provide numerous services to local residents, including aesthetics, recreation, and potable water. The results of hedonic studies of surface water quality can reflect improvements in any of the services provided.² Ground water, on the other hand, provides a much more limited set of services to local residents with the primary (and sometimes exclusive) service being a source of potable water.

The literature on the effects of ground water quality on residential property values consists of only a few rigorous studies.³ Contamination of ground water is often difficult to detect, and its impacts on health are often negligible for individuals whose homes rely on public water supplies. In early studies, Malone and Barrows (1990), Page and Rabinowitz (1993), and Dotzour (1997) found no significant relationship between contaminated ground water and property prices. Those studies make valuable contributions, but their econometric identification strategies—simple case study comparisons, two-sample t-tests of mean prices, and limited regression analyses of cross-sectional data—are now fairly dated. In addition, the ground water data available at the time were relatively scant, leading to issues associated with small sample sizes and coarse measures of water quality.

More recently, Case et al. (2006) used a hybrid repeat-sales/hedonic technique and found an average decrease of 4.7 percent in prices for residential condominiums impacted by ground water contamination but only after knowledge of the contamination was public. Boyle et al. (2010) found a temporary but significant 0.5–1.0 percent decline in home values for each 0.01 milligrams per liter (mg/l) of arsenic above the regulatory standard at

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

² A notable exception is Des Rosiers, Bolduc, and Theriault (1999), who specifically examined the impact of advisories regarding the quality of public drinking water on home prices.

³ Others have explored the impact of contaminated ground water on agricultural parcels where irrigation is the primary concern (Buck, Auffhammer, and Sunding 2014).

the time of 0.05 mg/l. Due to data constraints, both studies relied on spatially aggregated measures of contamination.

In contrast, Guignet (2013) compiled a unique set of data on tests of private ground water wells and linked the tests to individual home sales. The water quality tests serve as a clear signal to households and provide a clean home-specific measure of the disamenity. Guignet found that simply testing a home's well for contamination reduced the value of the home by an average of 11 percent regardless of whether contamination was found. A somewhat-larger 13 percent depreciation was found when the tests revealed levels of contamination that exceeded the regulatory standard, but caution is warranted when interpreting this result because there were only ten such transactions.

The current study builds on past works by using a rich data set of well-contamination tests conducted and compiled by FDH for the state of Florida from the 1980s through 2013. These data allow us to link ground water contamination levels in private wells to individual homes and thus conduct a detailed investigation into how home prices vary with home-specific pollutant concentrations. To our knowledge, this is only the second hedonic study (the other is Malone and Barrows (1990)) of how total nitrate and nitrite, along with other contaminants associated with surrounding agricultural activities, affects home values.

Background: Agriculture and Ground Water in Florida

Approximately 90 percent of Florida residents depend on ground water for drinking water (Southern Regional Water Project (SRWP) 2015). Florida is also particularly vulnerable to ground water contamination because the hydrology of the state is characterized by a high water table and thin layer of surface soil (SRWP 2015). Contributing to the risk are numerous point and nonpoint sources of pollution throughout the state, including a considerable threat posed by agriculture-related activities (SRWP 2015).

Florida is an important contributor to overall agricultural production in the United States and ranks among the top states in production of citrus crops and other fruits and vegetables (Florida Department of Agriculture and Consumer Services (FDACS) 2012). We analyze Lake County, which has a long history of citrus farming and other agricultural activities (FDACS 2012, Furman et al. 1975). The county sits in the central region of the state, which produces the majority of Florida's citrus crops (FDACS 2012). In 2012, Lake County produced the tenth largest volume of citrus crops in Florida and ranked eleventh in terms of acres devoted to commercial citrus production (FDACS 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/field crops.⁴ Although the county's soils are suitable for citrus groves, they do not offer enough nutrients to citrus crops without heavy fertilization and, as in surrounding counties, the soils are highly permeable and allow ground water to percolate quickly into the aquifer (Furman et al. 1975).

According to the FDH's database of potable-well tests, the most common pollutants found in ground water in Lake County are total nitrate and nitrite (N + N), ethylene dibromide (EDB), and arsenic (see Figure 1), all linked to use of agricultural fertilizers, pesticides, herbicides, and/or soil fumigants (Chen et al. 2001, Harrington, Maddox, and Hicks 2010, Solo-Gabriele et al. 2003, EPA 2014a, 2014b), as well as other sources.

Sources of N + N in ground water include human wastewater and animal manure but fertilizer use is the most prominent contributor (Harrington, Maddox, and Hicks 2010). Infants exposed to high levels of N + N in drinking water can suffer from blue baby syndrome, a blood disorder that leads to low oxygen levels and can be fatal (EPA 2014b). Consequently, EPA and the State of Florida have set a health-based maximum contaminant level (MCL) for N + N in drinking water of 10,000 parts per billion (ppb).

Sources of arsenic in Lake County include run-off from agriculture, production of electronics, and erosion of natural arsenic deposits. EDB enters ground water through spills of leaded gasoline, leaking storage tanks, and wastewater from chemical production; but EDB was also used at one time as a pesticide (EPA 2014a) and incidents of EDB contamination in the county are often attributed to agricultural activities (Florida Department of Environmental Protection (FDEP) 2014). Consumption of water contaminated with high levels of EDB and arsenic increases the risk of a number of adverse health conditions, including cancer, skin damage, and circulatory, digestive, and reproductive problems (FDH 2014, EPA 2014a). Florida's current MCLs are 10 ppb for arsenic and 0.02 ppb for EDB (stricter than the 0.05 ppb standard for EDB set by EPA).

If contamination in a well is found to exceed the MCL or Florida's health advisory level (HAL) for any contaminant, households are advised not to consume the water, and FDEP's Water Supply Restoration Program takes actions to expeditiously restore or otherwise provide safe potable water and covers the cost of those actions, which include temporary provision of bottled water followed by more-permanent solutions such as installation of a filter or provision of a connection to the public water line (FDEP 2014).

⁴ The land areas are calculated using geographic information system (GIS) data from the Florida Fish and Wildlife Conservation Commission (see http://ocean.floridamarine.org/TRGIS/Description_Layers_Terrestrial.htm#ag).

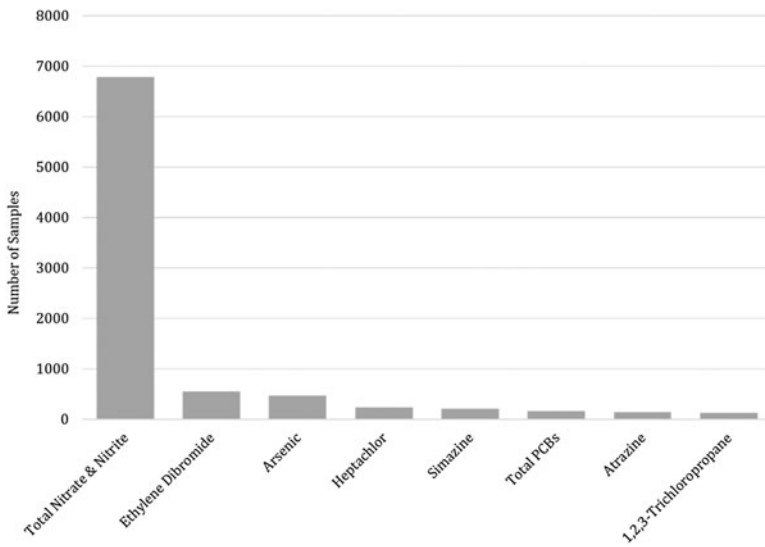


Figure 1. Most Frequent Ground Water Contaminants Detected in Lake County, Florida

Empirical Model

We estimate hedonic regression models of property values in which 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 a house’s structure (e.g., its age, interior square footage, and number of bathrooms), the parcel (e.g., lot acreage), and its location (e.g., the distance to urban centers and agricultural sites and whether it is located on the waterfront), all denoted by \mathbf{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 (\mathbf{M}_t). Of particular interest are measures of contamination in the potable well at home *i*, which are denoted by $f(test_{ijt}, \mathbf{ppb}_{ijt})$, a function of an indicator variable for whether the well at home *i* was recently sampled and tested ($test_{ijt}$) and the vector of pollutant concentration results (measured in ppb) from those tests (\mathbf{ppb}_{ijt}). The equation to be estimated is

$$(1) \quad \ln p_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta} + \mathbf{M}_t\boldsymbol{\alpha} + f(test_{ijt}, \mathbf{ppb}_{ijt}) + v_j + \varepsilon_{ijt}$$

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 of the time-invariant price effects associated with neighborhood (the block group) *j* and

allow ε_{ijt} to be correlated within each block group. The coefficients to be estimated are β , α , and v_j and coefficients related to $test_{ijt}$ and ppb_{ijt} , which vary depending on the functional form.

A common criticism of hedonic applications is that it is not always clear whether home sellers and buyers actually consider or are even aware of the environmental disamenity of interest and the measure employed on the right-hand side of the hedonic price equation (Guignet 2013). If they are not, there is no reason to think that prices capitalize the disamenity. In our context, however, at least some households are aware of ground water pollution in private wells through cases identified by FDH. When FDH suspects the presence of contamination, it asks for permission from homeowners to test the wells in person and mails the results of the tests to the homeowners, along with a letter that explains how to interpret the results. In addition, sellers in Florida who obtain drinking water from a private well are required by law to disclose the source of the home's drinking water, the date of the last water test, and the results of that test (Florida Association of Realtors 2009). Thus, $test_{ijt}$ and ppb_{ijt} are directly observed by sellers and likely by buyers as well.

Previous studies have found that regulatory standards for contaminants can serve as points of reference for households and that property values respond to the level of contamination in ground water relative to the standards (Boyle et al. 2010, Guignet 2012, 2013). When FDH sends the results of a well test to a homeowner, it categorizes the results as (i) exceeding either the federal MCL or Florida's HAL, (ii) exceeding Florida's secondary drinking-water standards, which reflect nuisance-based concerns unrelated to health, and (iii) exceeding the detectable limit but falling below the current standards.

In our base models, we therefore model $f(\cdot)$ following a similar categorization scheme involving a series of indicator variables:

$$(2) \quad f(test_{ijt}, ppb_{ijt}) = test_{ijt}\theta_{test} + \theta_{DL}\mathbb{1}(ppb_{ijt} > 0) + \theta_{MCL}\mathbb{1}(ppb_{ijt} > \mathbf{MCL})$$

where $\mathbb{1}(ppb_{ijt} > 0)$ is an indicator variable equal to one when any contaminants were found to be present (exceed the detectable limit) and zero otherwise and $\mathbb{1}(ppb_{ijt} > \mathbf{MCL})$ denotes whether any contaminants were at levels that exceeded the corresponding MCL or HAL.⁵ The variables $test_{ijt}$, $\mathbb{1}(ppb_{ijt} > 0)$, and $\mathbb{1}(ppb_{ijt} > \mathbf{MCL})$ are based on all tests taken within a temporal window of Δt years before the transaction, and the variations of θ are coefficients to be estimated.

⁵ We do not account for the secondary standards because some contaminants are not subject to a secondary standard and there were few observations in which a concentration exceeded the secondary standard but fell below the MCL/HAL.

We calculate the percent change in home sale price associated with testing of wells and the results of those tests as⁶

$$(3) \quad \% \Delta p_{test} = (e^{\theta_{test}} - 1) \times 100.$$

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

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

The hedonic analysis focuses on all homes that had been tested at any point prior to the sale. Therefore, $\% \Delta p_{test}$ is the percent change in the price of homes for which wells had been recently tested and no contamination had been found relative to homes for which the wells had been tested in the more distant past, all else constant. Similarly, $\% \Delta p_{DL}$ and $\% \Delta p_{MCL}$ are the percent changes in prices associated with tests that found that at least one contaminant exceeded the detectable limit or the MCL/HAL, respectively. Again, this is relative to homes for which wells had been tested for contamination in the distant past but not recently. When contamination is found, FDH continues to test until the situation is resolved (i.e., the levels remain below the MCL/HAL for an extended period of time or a permanent uncontaminated water supply is provided). Consequently, we argue that tests are no longer warranted for this counterfactual group of homes because ground water contamination is no longer a concern.

We can also change the counterfactual for the price comparison—for example, the impact on property values of contamination exceeding the detectable limit relative to homes that had been tested recently and no contamination had been found:

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

Equations 1 through 6 are estimated using several variants of the hedonic regression. One specification incorporates spatial (block group) fixed effects

⁶ Calculation of the percentage changes is based on Halvorsen and Palmquist (1980) and is necessary with a logged dependent variable and a binary independent variable. Alternative calculations include those of Kennedy (1981), who developed an approximate unbiased estimator of the percentage impact of a dummy variable, and of van Garderen and Shah (2002), who developed an exact unbiased estimator. We also estimated the percentage change in price using those approaches and found only miniscule differences in the results.

and another distinguishes between contamination that exceeds the minimum detectable limit and contamination that exceeds the MCL/HAL.

As with most hedonic applications, there is concern that there may be spatially dependent unobserved influences that affect property values. For example, many neighborhoods are 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, lenders use recent comparable sales of nearby homes to determine the value of a property for mortgage purposes. Failure to control for such spatial dependence can result in potentially biased or inconsistent estimates.

To test for spatial dependence, we use the robust Lagrange multiplier test of both the spatial error and the lag format (LeSage and Pace 2009). The spatial lag of the dependent variable takes the following form:

$$(7) \quad \ln p_{ijt} = \rho wp_{[ijt]} + \mathbf{x}_{ijt}\boldsymbol{\beta} + \mathbf{M}_t\boldsymbol{\alpha} + f(\text{test}_{ijt}, \mathbf{ppb}_{ijt}) + v_j + \varepsilon_{ijt}$$

where ρ is a spatial lag parameter to be estimated and $wp_{[ijt]}$ is the corresponding element from the $n \times 1$ vector obtained after multiplying the spatial weight matrix (SWM), \mathbf{W} , by the price vector, \mathbf{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 instead models unobserved spatial dependence in the error term as

$$(8) \quad \ln p_{ijt} = \mathbf{x}_{ijt}\boldsymbol{\beta} + \mathbf{M}_t\boldsymbol{\alpha} + f(\text{test}_{ijt}, \mathbf{ppb}_{ijt}) + v_j + \varepsilon_{ijt}$$

$$\text{where } \varepsilon_{ijt} = \lambda w\varepsilon_{[ijt]} + u_{ijt}.$$

In this specification, λ is the spatial autocorrelation parameter to be estimated, $w\varepsilon_{[ijt]}$ is the corresponding element from the $n \times 1$ vector obtained after multiplying \mathbf{W} by the vector of error terms $\boldsymbol{\varepsilon}$, and $u_{ijt} \sim N(0, \sigma^2)$.⁷

Robust versions of the spatial lag and error Lagrange multiplier tests were used to test for spatial dependence and to choose between the lag and error models. In all cases, the null hypothesis of no spatial dependence was

⁷ We explored a variety of SWMs used in spatial econometrics to exogenously specify the spatial relationships between neighboring home sales. We favored SWMs that identified neighbors based on distance and time so that nearby and more-recent home sales would be given nonzero weights. We used time constraints of six, twelve, and eighteen months prior to a transaction and included three months after a transaction to account for delays between contracts and sales. The spatial radii used to identify neighbors were 800, 1,600, and 3,200 meters. The inverse distance between two homes is used as the individual entry in the matrix, which is row-standardized so the weights corresponding to each transaction sum to one (LeSage and Pace 2009).

rejected and the spatial error models in each format had significantly larger Lagrange multiplier coefficients, supporting use of the spatial error format. Due to concern about simultaneous lag and error dependence, we also estimated the general spatial model (LeSage and Pace 2009), which includes both a spatial lag of the dependent variable and 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 percent level. Together, these tests demonstrate that the spatial error model best reflects the spatial nature of the underlying data-generation process.⁸

Data

We analyze transactions of single-family homes in Lake County (just west of Orlando) from 1990 through 2013. Lake County was chosen because concerns there about ground water pollution relate primarily to the run-off of chemicals associated with agricultural activities, and a preliminary examination of the data suggested that Lake County provided a sufficient number of well tests for the regression analysis.

Well Test Samples

FDH regularly tests ground water wells for contamination and maintains a database of all wells identified and tested and the results of those tests. The tests are conducted for a variety of reasons, but in most cases FDEP notifies FDH of potential contamination caused by human activities.⁹ FDH then asks for permission from the property owner to test the well and cannot test it without the owner's consent. Given these procedures, testing of wells in the sample may potentially be endogenous. Owners who plan to put their houses on the market and believe that contamination exists, for example, could refuse to allow the wells to be tested because they would then have to disclose contamination to potential buyers. If this is a common occurrence, the hedonic estimates could be biased since the level of contamination and probability of a test would be correlated. Some owners have refused, but the vast majority of them have agreed to have their wells tested.¹⁰

⁸ Following LeSage and Pace (2009), we selected the SWM with the highest log-likelihood in the majority of the models, which used a radius of 3,200 meters and a temporal window of twelve months. However, the differences between SWMs were all minimal.

⁹ FDH's water testing program focuses on contamination caused by human activities and generally does not investigate contamination from natural causes. Some issues are later determined to have had a natural cause.

¹⁰ Of the 6,619 private drinking-water wells in Lake County identified by FDH, only 365 had no recorded tests (5.5 percent). The lack of testing for those wells could be related to owners who refused testing. These untested wells could also belong to homes that had multiple wells and only one well was tested.

Our analysis focuses only on homes that were tested at some point prior to being sold, which essentially circumvents selection concerns. The comparisons in our regressions are of homes that FDH had already identified in terms of potential contamination, and the owners had an incentive to continue to allow testing until the water was found to be clean or an alternative clean water supply was provided.

In any case, it is clear that the well test data used in this study are not random and should not be interpreted as a representative sample of ground water quality. Nonetheless, these data are useful for identifying how property values may respond to contamination in private wells.

We carefully matched tests at private potable wells to corresponding residential parcels and transactions. The data-matching procedure relied on both 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 techniques were used together to provide the most accurate links possible. Using this procedure, we were able to match 6,619 private potable wells to a home.¹¹ A total of 6,652 water samples had been taken from those wells, the earliest in 1983 and the most recent in 2013 (several wells were sampled more than once). As shown in [Figure 1](#), N + N, EDB, and arsenic were the three most commonly detected contaminants.

Residential Transactions

There were 124,859 arms-length transactions of single-family homes in Lake County from 1990 through 2013.¹² Of those unique sales, 5,738 involved parcels for which a well had been tested at any time. Our final data set was comprised of the 1,730 transactions where a well had been tested prior to the sale. We use this subset rather than the broader set of transactions for two reasons. First, there is an observed level of contamination, even if zero, for every transaction in the sample. Testing under other programs could reveal contamination, but that information was not available and could otherwise confound the results. Prior hedonic studies of ground water contamination have taken a similar approach (Malone and Barrows 1990). Second, a series of t-tests comparing the sample means across all of the observed house and parcel characteristics suggested that the tested homes were significantly different from the homes where wells had never been tested. Similar, but slightly less stark, differences were found when we

¹¹ See the appendix in Guignet, Northcutt, and Walsh (2015) for details.

¹² The data on the residential parcels, their characteristics, and the transactions were obtained from the Lake County Property Appraiser's Office. Transactions of homes that were shown as having more than twelve bathrooms or that had plots exceeding 50 acres were omitted, as were sales for which the real price in 2013 U.S. dollars was in the top or bottom one percentile.

compared our sample of home sales to those that were tested only after they were sold. If such differences also exist with respect to unobserved attributes, the results could be biased. Our sample of 1,730 sales consisted of a relatively homogenous set of homes.¹³

Table 1 shows that 1,135 of the 1,730 transactions had tests that revealed concentrations of contaminants that exceeded the detectable limit (denoted as *above DL*). The concentration of at least one of the contaminants exceeded the applicable MCL or HAL (hereafter denoted simply as *above MCL*) for 180 of those transactions. The number of identifying observations decreases when we consider shorter temporal windows in terms of the number of years prior to the transaction ($0 \leq \Delta t \leq 1, 2, \text{ or } 3$ years). The main hedonic analysis focuses on ground water pollution found within three years ($0 \leq \Delta t \leq 3$) of the transaction date. This timeframe was chosen based on the number of identifying sales available for statistical analysis versus the amount of time one can reasonably expect contamination information to remain available and relevant to buyers and sellers.¹⁴ Nonetheless, we also investigated the most appropriate temporal window. Descriptive statistics for the maximum concentrations of the three most common contaminants found three years prior to the sale dates are shown in Table 2.

To identify impacts on property values properly, we must control for other characteristics of the housing bundle that may influence price. We include the following home structure characteristics: 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 a home's location relative to amenities and disamenities also explains variations in home values, we include several location characteristics: the number of gas stations within 500 meters; distances to the nearest primary road, golf course, and protected open space; whether the home is a lakefront property; and whether it is located in a floodplain. To control for confounding factors associated with proximity to likely sources of pollution, we include the inverse distance to two types of agricultural land—citrus groves and row/field crops.¹⁵ We also account for whether a home is located in the service

¹³ The 1,730 homes where testing took place prior to the sale were more homogenous than the broader sample, but significant differences remained for the sample means of eight of the eighteen variables shown in Table 3. There also could have been differences in unobserved attributes. However, we found that our hedonic estimates were robust when we used matched samples based on several propensity score matching techniques, including nearest neighbor with and without replacement and kernel matching.

¹⁴ In a hedonic analysis of potable well contamination, Boyle et al. (2010) found that housing prices rebounded after three years.

¹⁵ The variables were derived from GIS data from Lake County and the Florida Fish and Wildlife Conservation Commission, the U.S. Census Bureau's 2010 TIGER/Line files, Navteq 2009 and 2012 auto service data, the U.S. Geologic Survey's 2012 Gap Analysis Program, and FEMA's 2012 national flood hazard layer.

Table 1. Number of Sales in which Private Wells Were Tested

Number of Wells	Time before Sale Date			
	0-1 Year	0-2 Years	0-3 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

area of an existing public water system.¹⁶ Descriptive statistics for the housing-structure and spatial characteristics are presented in [Table 3](#).

Results

We estimated hedonic regressions using all 1,730 transactions from 1990 through 2013 where data on potable well contamination prior to the sale were available. This is a rather long period over which to impose a single hedonic surface (and thus a constant equilibrium), but we viewed it as an acceptable tradeoff given the relatively small size of our sample. All regressions included year and quarter dummy variables to account for overall housing market trends.

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The results of the base hedonic model for wells tested within three years prior to sale are presented in [Table 4](#). All of the variables from [Table 3](#) were included

Table 2. Summary of Pollutant Concentrations in Parts per Billion

Contaminant	Observations	Average	Min.	Max.	MCL / HAL
Total nitrate + nitrite	477	3,746.187	15	22,000	10,000
Ethylene dibromide	20	0.0701	0.0027	0.46	0.02
Arsenic	22	4.0706	0.1160	23.6	10

Note: These figures consider transactions in which the potable well was tested within three years prior to the sale date and concentrations of the corresponding contaminant were detected.

¹⁶ In some areas of Florida, a number of homes within public water service areas are not connected to public water and use private wells instead. The data on public water service areas were obtained from the St. Johns River Water Management District.

Table 3. Descriptive Statistics for Home and Location Characteristics

Variable	Number of Observations	Mean	Std. Dev.	Min.	Max.
Price of home in 2013 U.S. dollars	1,730	257,203	120,984	20,713	571,359
Age of home in years	1,701	12.53	15.30	0	123
Number of bathrooms	1,730	2.20	0.69	1	7
Interior square footage	1,730	2,032	780	396	6,558
Lot size in acres	956	2.10	2.40	0.13	15.16
Quality of construction (50–950)	1,730	583.49	79.06	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 in kilometers	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 in meters to:					
Nearest protected area	1,730	1,874	1,504	12,7204	6,553
Nearest primary road	1,730	1,1177	6,415	150	24,140
Nearest lake or pond	1,730	340	271	0	2,132
Nearest citrus grove	1,730	365	385	0	5,816
Nearest row/field crop	1,730	250	241	0	1,735
Nearest golf course	1,730	2,645	2,786	19	17,722
In public water system service area	1,730	0.1844	0.3879	0	1
<i>N</i> = 1,730 sales					

Notes: All characteristics are dummy variables unless otherwise noted. Construction quality is based on county assessor gradings in which 50 is poorest quality and 950 is best quality.

in the regressions but we report only the estimates of interest.¹⁷ The other coefficient estimates all displayed the expected sign or were insignificant. The

¹⁷ The only exception is that the distance to the nearest major road was excluded due to concerns about multicollinearity; the estimates of interest are robust to that exclusion. Lot size and interior square footage entered in log form, and we used the inverse distance to the nearest citrus grove, row crop, and golf course instead of linear distance. Companion dummy variables were included to account for missing values for lot size, number of bathrooms, and age of the home.

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

Variable	Base Model				Base Model plus Additional Interaction Term			
	OLS (A)	FE (B)	SEM (C)	SEM + FE (D)	OLS (A1)	FE (B1)	SEM (C1)	SEM + FE (D1)
Tested	-0.0239 (0.0189)	0.0021 (0.0188)	-0.0220 (0.0172)	0.0022 (0.0170)	-0.0239 (0.0189)	0.0020 (0.0189)	-0.0220 (0.0172)	0.0020 (0.0170)
Tested × Above DL	-0.0146 (0.0181)	-0.0276 (0.0173)	-0.0150 (0.0182)	-0.0277 (0.0179)	-0.0145 (0.0181)	-0.0288 (0.0177)	-0.0150 (0.0185)	-0.0289 (0.0181)
Tested × Above MCL	— —	— —	— —	— —	-0.0007 (0.0400)	0.0153 (0.0379)	-0.0004 (0.0367)	0.0155 (0.0354)
Lambda (λ)	— —	— —	0.1040*** (0.0145)	0.0490*** (0.0119)	— —	— —	0.1040*** (0.0145)	0.0490*** (0.0119)
$\% \Delta p_{test}$	-2.36 (1.84)	0.21 (1.89)	-2.17 (1.68)	0.21 (1.70)	-2.36 (1.84)	0.20 (1.89)	-2.17 (1.68)	0.20 (1.70)
$\% \Delta p_{test \rightarrow DL}$	-1.45 (1.79)	-2.73 (1.68)	-1.49 (1.79)	-2.73 (1.74)	-1.44 (1.78)	-2.84* (1.72)	-1.49 (1.82)	-2.85 (1.76)
$\% \Delta p_{DL}$	-3.77*** (1.32)	-2.52** (1.23)	-3.63*** (1.31)	-2.52* (1.33)	-3.77*** (1.35)	-2.65** (1.33)	-3.63*** (1.35)	-2.65** (1.36)
$\% \Delta p_{MCL}$	— —	— —	— —	— —	-0.07 (4.00)	1.55 (3.85)	-3.66 (3.47)	-1.13 (3.46)
Observations	1,730	1,730	1,730	1,730	1,730	1,730	1,730	1,730
Block-group fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Continued

Table 4. Continued

Variable	Base Model				Base Model plus Additional Interaction Term			
	OLS (A)	FE (B)	SEM (C)	SEM + FE (D)	OLS (A1)	FE (B1)	SEM (C1)	SEM + FE (D1)
No. of fixed effects	—	65	—	65	—	65	—	65
R-squared	0.7981	0.7701	0.8001	0.8224	0.7981	0.7702	0.8001	0.8224

Note: The dependent variable is the natural log of the real transaction price (2013 U.S. dollars). 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*). *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. Robust standard errors are provided in parentheses. In the block-group FE models, standard errors are clustered at the block-group level. Models C, D, C1, and D1 are spatial error models (SEMs) in which the error terms are allowed to be spatially correlated based on inverse-distance SWMs with a distance radius of 3,200 meters and a time constraint of twelve months (see the empirical model for details).

adjusted R-square ranged from 0.770 to 0.822, indicating a fairly good overall statistical fit.

In the ordinary least squares (OLS) model (A), testing for contamination within three years prior to the sale (*tested*) and contamination exceeding the detectable level (*above DL*) are negatively correlated with home prices, but both coefficients are small and statistically insignificant.

The second panel in Table 4 shows the estimated percent changes in price ($\% \Delta p$) as calculated in equations 3 through 6. Testing for ($\% \Delta p_{test}$) and finding (conditional on testing) contamination ($\% \Delta p_{test \rightarrow DL}$) do not individually have significant effects on home prices. When considered jointly ($\% \Delta p_{DL}$), however, their impact is statistically significant. Testing *and* finding contamination within three years prior to the sale suggests a 3.77 percent decline in price. Similar results are generated by the second model (B), which incorporates block-group fixed effects (FE) to account for all time-invariant price effects associated with a particular neighborhood (block group). In both models, the only significant price differential is for $\% \Delta p_{DL}$, which points to a depreciation of 2.52 percent and 3.77 percent.¹⁸ Multiplying $\% \Delta p_{DL}$ by the mean price of \$258,238 for homes that were tested more than three years prior to being sold and thus where any past contamination issues had since been resolved (since FDH no longer deemed it necessary to continue to monitor the well) suggests an average loss of \$6,505 and \$9,746.

Model C is a spatial error model (SEM) that better controls for the spatial nature of the underlying data-generation process (LeSage and Pace 2009). It incorporates a SWM with a distance constraint of 3,200 meters and a time constraint of twelve months. The coefficients from this model are comparable to the ones from the OLS model with minor differences in magnitude. The significant spatial-autocorrelation coefficient λ demonstrates that the error terms are spatially correlated. In this model, the combined impact of a well being tested and contamination found (above the detectable level) is a 3.63 percent reduction in value, which amounts to a mean loss of \$9,374 and is significant at the 99 percent level. Model D adds block-group fixed effects to model C, and the results are similar to those from the nonspatial FE specification in model B.¹⁹

¹⁸ These results are robust to alternative temporal windows; $0 \leq \Delta t \leq 1, 2, \text{ and } 3$ all yield estimates for $\% \Delta p_{DL}$ of a 2.2 percent to 3.8 percent decline in value. When propensity score matching techniques are used, the resulting estimates of the change in price are similar—losses of 3.6 percent to 5.5 percent depending on the matching technique.

¹⁹ We also estimated block-group FE regression models that allowed the standard errors to be clustered based on both the census block group and year to address concerns about correlation in the same year and to follow recommendations of Boyle et al. (2012). Those coefficient estimates were nearly the same as the estimates from the other FE models but had slightly larger standard errors. The estimates of $\% \Delta p_{DL}$ were robust to this alternative clustering. The only difference was that the previously marginally significant $\% \Delta p_{test \rightarrow DL}$ effect in model B1 became insignificant. However, there were not enough clusters of both time and space to calculate the full model using this specification so we did not carry it forward.

In models A1 through D1, we add an interaction term to investigate whether contamination that exceeds the MCL/HAL is associated with an additional decrease in value.²⁰ 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 FDEP at no cost to the homeowner when the MCL/HAL is exceeded (FDEP 2014). That said, the lack of significant results could be partially due to the small number of transactions where the MCL/HAL was exceeded (48).

In all four models (A1 through D1), we find that $\% \Delta p_{DL}$ equals a depreciation of 2.65 percent to 3.77 percent, again suggesting that recent testing and detection of contamination in a private well corresponds to a small but significant decrease in home values. Since the estimates from the spatial models are similar to, and fall within the range of, the estimates from the nonspatial OLS and FE models, we focus on the OLS and FE models in the remainder of the analysis.

Impacts on Property Values over Time

We next investigate whether impacts of ground water testing and contamination are permanent or diminish over time. We re-estimate models A and B, and instead of including one effect for testing of zero to three years, we include *tested* and *above DL* indicators for each of eight years prior to the sale date. By accounting for the indicators in one-year increments using the same hedonic regression, we examine how $\% \Delta p_{DL}$ varies over time. The estimates are calculated following equation 4 and the results are presented in Figure 2.

The OLS and FE models suggest that a test and finding of contamination within one year of the sale is associated with a 5.94 percent and 3.75 percent reduction in the value of a home, respectively. In addition, we find a significant 5.81 percent decline associated with testing and contamination within two to three years prior to the transaction in the OLS model. Otherwise, none of the price impacts are statistically significant. The estimates are also not generally statistically different across the years. Only one difference is significant. Pairwise nonlinear Wald tests of the $\% \Delta p_{DL}$ estimates in year 1 in both models and year 3 in the OLS model suggest that those estimates are statistically different from the insignificant estimates in year 8. In general, as Figure 2 illustrates, the point estimates gradually tend toward zero and the 95 percent confidence intervals widen when considering testing and contamination found more than three years prior.²¹

²⁰ Note that our notation commonly refers to the regulatory standard as MCL. We use MCL to refer to both EPA's MCL and Florida's more stringent HAL when applicable.

²¹ Consistent with these results, we also explored specifications with a continuous "years since a test" variable, which suggested a positive and marginally significant linear relationship with

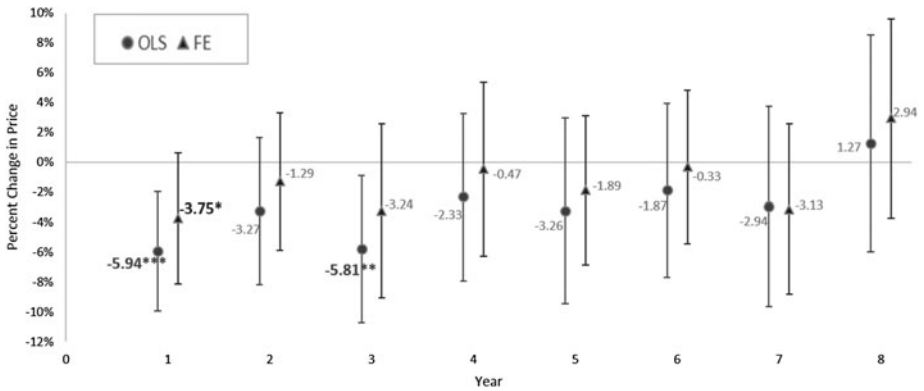


Figure 2. Price Impacts of Testing and Contamination over Time

Notes: *** denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$. The figure presents estimates of $\% \Delta p_{DL}$ by year from two hedonic regression models: OLS denoted by circles and block-group FEs denoted by triangles. The x-axis denotes 0–1 years, 1–2 years, 2–3 years, ..., 7–8 years. Vertical lines represent the 95 percent confidence intervals.

As previously noted, FDH generally continues to test private wells until the level of contamination remains below the MCL/HAL for an extended period of time or, in some cases, until a permanent clean water supply is provided (such as by a connection to the public water system). Our results suggest that property values are 3–6 percent lower for homes where recent tests revealed contamination and provide some evidence that the decreases are not permanent and potentially dissipate within a few years. The fact that any price effects seem to diminish over time suggests that prices may rebound once contamination issues have been resolved and perhaps that information about contamination becomes less relevant and/or available to buyers and sellers over time.

Heterogeneity across Contaminants

To examine whether impacts on property values vary based on the type of contaminant, we re-estimate the OLS and FE models with a series of additional interaction terms to allow the individual price effect of each of the most common pollutants (N + N, EDB, and arsenic) to vary from the price effect of contamination in general. The results are omitted for brevity, but in short we find no statistically significant differences in the price impacts of N + N, EDB, and arsenic relative to contamination in general. These results must be interpreted with caution, however. As shown in [Table 2](#), the number

coefficient size ranging from 3.5e-03 to 3.7e-03. Interactions with *above DL* and *above MCL* were insignificant.

of transactions available for statistical identification when looking at individual contaminants is quite small, at least for EDB and arsenic.

Concentration of Total Nitrate and Nitrite

The data set included a relatively large number of transactions in which detectable levels of N + N were found in tests within three years before the sale dates (see Table 2), which allowed us to explicitly examine how the impacts on price might vary with increasing levels of N + N in wells. We re-estimated models A and B to include the maximum concentration of N + N found within three years before a transaction (ppb_{ijt}^{NN}). Different functional forms of the relationship between $\ln p_{ijt}$ and ppb_{ijt}^{NN} are assessed, including linear and piecewise-linear models.

Building on equations 3, 4, and 5, we use the coefficients from the re-estimated models to calculate the corresponding percent change in price ($\% \Delta p_{ijt}^{NN}$) as a function of ppb of N + N. First, consider a hedonic model in which the concentration of N + N enters linearly. The percent difference in price for a home with a recently tested well in which N + N was detected relative to a home with no recent test and no contamination detected is

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

where θ_{NN} denotes the slope coefficient corresponding to the concentration of N + N.

Figure 3 presents the estimated percent change in price as a function of N + N (ppb_{ijt}^{NN}) for the OLS and FE models. The linear specifications provide mixed results. There is a generally insignificant price effect and, if any, a counterintuitive positive relationship in the OLS model. The linear FE model, on the other hand, suggests the expected negative relationship, but the change in price does not become statistically different from zero until roughly the 10,000 ppb MCL.

To examine whether the 10,000 ppb health-based standard serves as a point of reference for buyers and sellers, we estimate piecewise-linear models where the slope coefficients at concentrations of N + N below and above the MCL are allowed to differ.²² The percent change in price in this case is estimated as

²² We also estimated models that allowed for a discontinuous break in the linear trend at 10,000 ppb and found no evidence of statistically significant price effects. In the OLS model, the point estimates suggested a drop in price at 10,000 ppb but the counterintuitive positive slope remained and the confidence intervals for N + N levels above the MCL were much larger and clearly overlapped zero. This is due, at least in part, to the small number of sales for which

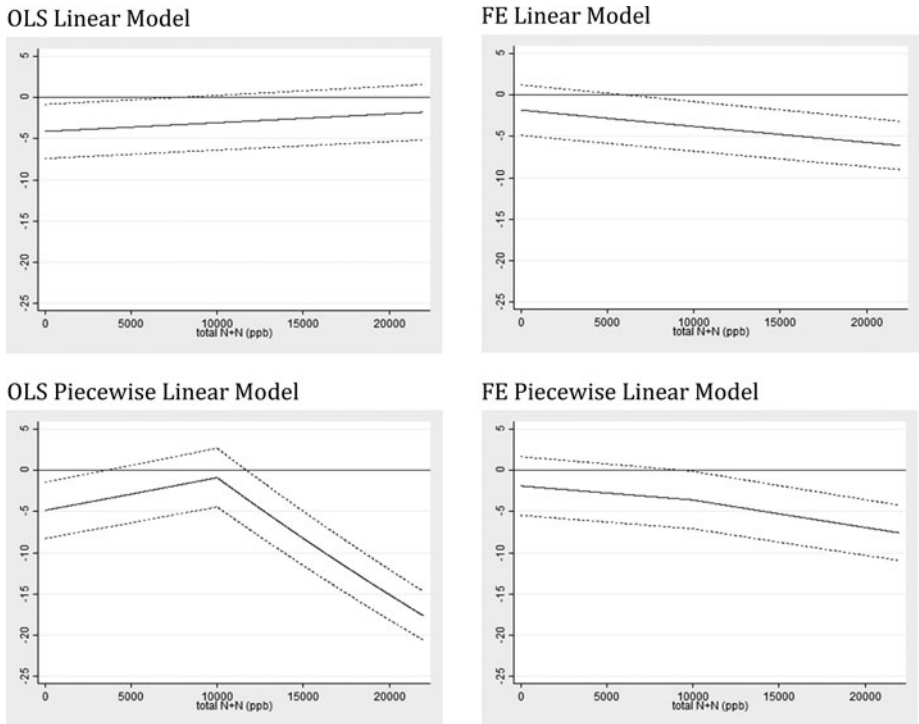


Figure 3. Percent Change in Price and Concentration of Total Nitrate and Nitrite: Tests and Contamination Zero to Three Years Prior to Sale

Notes: The concentration of total nitrate and nitrite (in ppb) is displayed on the x-axis, and the percent change in price is displayed on the y-axis (see equations 9 and 10). Dotted lines denote the 95 percent confidence intervals (derived using the *predictnl* command in Stata 14).

$$(10) \quad \% \Delta p_{ijt}^{NN} = \left(e^{\left\{ \theta_{rest} + \theta_{DL} + \left(\theta_{NN} \times ppb_{ijt}^{NN} \right) + \left(\theta_{NN_MCL} \times \left(ppb_{ijt}^{NN} - MCL \right) \times \mathbb{1} \left(ppb_{ijt}^{NN} > MCL \right) \right\}} - 1 \right) \times 100$$

where the additional parameter to be estimated, θ_{NN_MCL} , captures the change in the slope once the 10,000 ppb MCL is exceeded, which is denoted by the dummy variable $\mathbb{1} \left(ppb_{ijt}^{NN} > MCL \right)$. As shown in Figure 3, the price differential is generally insignificant when the N + N level remains below the MCL, but once it exceeds the MCL home values decline significantly. When the N + N

N + N exceeded the MCL (31). The corresponding block-group FE model showed little evidence of a discrete drop in prices, supporting the possibility of a linear relationship. As with the OLS model, the FE model produced much larger confidence intervals when N + N exceeded the MCL.

level is twice the MCL, for example, the average loss in value is \$38,900 in the OLS model and \$17,900 in the FE model.

Conclusion

As regulatory actions required by the Clean Water Act have further reduced point-source pollutants, attention has increasingly shifted to contamination from nutrients and other chemicals associated with agricultural fertilizers and pesticides.²³ Our hedonic study examines data for Lake County, Florida, where significant concern about pollution of ground water stems from run-off of chemicals associated with production of oranges and other agricultural activities. The most frequently detected contaminants observed in the data are total nitrate and nitrite (N + N), ethylene dibromide (EDB), and arsenic, which have been linked to agricultural fertilizers, pesticides, herbicides, and soil fumigants (Chen et al. 2001, FDEP 2014, Harrington, Maddox, and Hicks 2010, Solo-Gabriele et al. 2003, EPA 2014b). Human exposure to these contaminants can increase infant mortality and the risk of developing a number of adverse health conditions, including blue-baby syndrome, cancer, and liver, stomach, circulatory, and reproductive issues (EPA 2014b).

Only a few hedonic studies have rigorously examined how home values are affected by changes in ground water quality (Boyle et al. 2010, Guignet 2013). We attribute this gap in the literature largely to a lack of appropriate data and difficulties associated with linking measures of ground water quality to individual homes and transactions. We use a comprehensive data set of contamination tests of potable wells conducted by the Florida Department of Health. Our dual data-matching procedure uses property and well address fields with spatial coordinates and parcel boundaries to establish accurate matches and ultimately link residential transactions to well tests and contaminant levels relative to the sale dates. This unique data set allows us to investigate how property values vary with home-specific levels of contamination in private potable water wells, thus providing insight for benefit-cost analyses of policies meant to improve and protect ground water quality.

We compare sales for homes where the private wells have been tested for contamination at some point prior to being sold using hedonic regressions. We find that identification of contamination in a well within three years of a

²³ In EPA's 2000 National Water Quality Inventory (www.epa.gov/waterdata/2000-national-water-quality-inventory-report-congress), states reported that agricultural nonpoint-source pollution was the leading source of water quality impacts for surveyed rivers and lakes, the second largest source of impairments to wetlands, and a major contributor to contamination of surveyed estuaries and ground water. The most recent report (2004) does not go into as much detail and simply labels the leading cause as "agriculture." Furthermore, a recent survey of 40 private wells in New York found that several contained quantifiable traces of agricultural pesticides (Richards et al. 2012). A review of recent studies of ground water contamination can be found in Sudarshan and Venkataraman (2013).

sale is associated with a 2–6 percent reduction in home values. The decrease in value is not permanent, however, and seems to diminish a few years after the contamination issue is resolved. This conclusion may also reflect, at least partially, that information about the contamination becomes less relevant and/or less available to buyers and sellers as time passes. Boyle et al. (2010) identified a similar rebound effect a few years after public information about ground water contamination was released.

We analyzed the three most common contaminants individually (N + N, EDB, and arsenic) and found no significant heterogeneity in how the housing market responds. However, those results are confounded by the small number of identifying transactions available. Further study of the individual effects of various contaminants could be valuable. If the price impacts are in fact similar across different pollutants and perhaps even sources, this would facilitate benefit transfer to other ground water contamination contexts, such as leaking underground storage tanks, hydraulic fracturing and natural gas extraction, and hazardous chemicals from superfund sites.

The significant number of wells in our data set that had been identified as contaminated with N + N allowed us to explicitly model how changes in home values vary at different concentrations of the contaminant. We found no significant impacts from relatively low concentrations. Once the health-based regulatory limit was exceeded, however, prices declined significantly. At twice the regulatory limit, we estimated a reduction in value of 7–15 percent, which translates to an average loss of \$17,900 to \$38,900. These results are in line with prior risk communication and valuation studies (Boyle et al. 2010, Guignet 2012, Johnson and Chess 2003, Smith et al. 1990), supporting the notion that given little knowledge of how pollution maps into health risks, households use the regulatory standard as a reference when forming their perceptions of risk. This finding also supports our overall analysis by demonstrating that households respond to information provided by regulators.

Our study adds to the small body of literature examining how residential property values are affected by ground water pollution by using more sophisticated statistical methods, exploiting both spatial and temporal variations in contamination, including a more-exhaustive set of control variables, and incorporating property-specific measures of contamination. Still, as in past studies, some statistical issues remain, and caution is warranted when interpreting the results. First, some of the conclusions are based on a relatively small number of identifying sales. Second, the analysis is limited to homes that were tested at some point prior to being sold. Our data diagnostics suggested that this sample of homes may differ from homes where the wells were never tested. Consequently, the external validity of our results is unclear, and extrapolation of the results to a broader population of homes may not be appropriate. Future studies could examine the potential endogenous selection of private well tests and establish a more viable causal link.

Despite its limitations, this study provides evidence of how home values might be impacted by ground water contamination and an estimated magnitude of those effects. Our results are consistent with findings from other recent studies in terms of magnitude and permanence (Guignet 2013, Boyle et al. 2010). With the preceding caveats in mind, our results provide useful information for policymakers considering actions to remediate ground water contamination or employ alternative mitigating and averting actions.

References

- Artell, J. 2013. "Lots of Value? A Spatial Hedonic Approach to Water Quality Valuation." *Journal of Environmental Planning and Management* 57(6): 862–882.
- Bin, O., and J. Czajkowski. 2013. "The Impact of Technical and Non-technical Measures of Water Quality on Coastal Waterfront Property Values in South Florida." *Marine Resource Economics* 28(1): 43–63.
- Boyle, K.J., N.V. Kuminoff, C. Zhang, M. Devanney, and K.P. Bell. 2010. "Does a Property-specific Environmental Health Risk Create a 'Neighborhood' Housing Price Stigma? Arsenic in Private Well Water." *Water Resources Research* 46(3) doi: 10.1029/2009wr008074.
- Boyle, K.J., L. Lewis, J.C. Pope, and J.E. Zabel. 2012. "Valuation in a Bubble: Hedonic Modeling Pre- and Post-housing Market Collapse." *AERE Newsletter* 32(2): 24–31.
- Boyle, M.A., and K.A. Kiel. 2001. "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities." *Journal of Real Estate Literature* 9(2): 117–144.
- Buck, S., M. Auffhammer, and D. Sunding. 2014. "Land Markets and the Value of Water: Hedonic Analysis Using Repeat Sales of Farmland." *American Journal of Agricultural Economics* 96(4): 953–969.
- Case, B., P.F. Colwell, C. Leishman, and C. Watkins. 2006. "The Impact of Environmental Contamination on Condo Prices: A Hybrid Repeat-sale/Hedonic Approach." *Real Estate Economics* 34(1): 77–107.
- Chen, M., L.Q. Ma, C.G. Hoogeweg, and W.G. Harris. 2001. "Arsenic Background Concentrations in Florida, U.S.A., Surface Soils: Determination and Interpretation." *Environmental Forensics* 2: 117–126.
- David, E.L. 1968. "Lakeshore Property Values: A Guide to Public Investment in Recreation." *Water Resources Research* 4(4): 697–707.
- Des Rosiers, F., A. Bolduc, and M. Theriault. 1999. "Environment and Value: Does Drinking Water Quality Affect House Prices?" *Journal of Property Investment and Finance* 17(5): 444–463.
- Dotzour, M. 1997. "Groundwater Contamination and Residential Property Values." *Appraisal Journal* 65(3): 279–285.
- Environmental Protection Agency. 2012a. "Private Drinking Water Wells." EPA, Washington, DC. Available at www.water.epa.gov/drink/info/well.
- . 2012b. "Public Drinking Water Systems: Facts and Figures." EPA, Washington, DC. Available at www.water.epa.gov/drink/info/well.
- . 2014a. "Basic Information about Ethylene dibromide in Drinking Water." EPA, Washington, DC. Available at www.water.epa.gov/drink/contaminants/basic information/ethylene-dibromide.cfm.
- . 2014b. "Drinking Water Contaminants." EPA, Washington, DC. Available at www.water.epa.gov/drink/contaminants/index.cfm.
- Florida Association of Realtors. 2009. "Seller's Real Property Disclosure Statement" (SRPD-4). Florida Association of Realtors, Orlando, FL. Available at <http://sdrhouses.com/FlatFeeDisclosure.pdf>.

- Florida Department of Agriculture and Consumer Services. 2012. "Florida Agriculture by the Numbers: 2012." FDACS, Tallahassee, FL.
- Florida Department of Environmental Protection. 2014. "Water Supply Restoration Program for Contaminated Potable Water Wells." FDEP, Tallahassee, FL. Available at www.dep.state.fl.us/water/wff/wsupply.
- Florida Department of Health. 2014. "Florida Department of Health Environmental Chemistry Analyte List." FDH, Tallahassee, FL. Available at www.floridahealth.gov/environmental-health/drinking-water/_documents/HAL_list.pdf.
- Furman, A.L., H.O. White, O.E. Cruz, W.E. Russell, and B.P. Thomas. 1975. "Soil Survey of Lake County Area, Florida." Natural Resources Conservation Service, USDA, Washington, DC. Available at www.nrcs.usda.gov/Internet/FSE_MANUSCRIPTS/florida/lakeareaFL1975/Lake.pdf.
- Gibbs, J.P., J.M. Halstead, and K.J. Boyle. 2002. "A Hedonic Analysis of the Effects of Lake Water Clarity on New Hampshire Lakefront Properties." *Agricultural and Resource Economics Review* 31(1): 39–46.
- Guignet, D. 2012. "The Impacts of Pollution and Exposure Pathways on Home Values: A Stated Preference Analysis." *Ecological Economics* 82: 53–63.
- . 2013. "What Do Property Values Really Tell Us? A Hedonic Study of Pollution from Underground Storage Tanks." *Land Economics* 89(2): 211–226.
- Guignet, D., R. Northcutt, and P.J. Walsh. 2015. "The Property Value Impacts of Groundwater Contamination: Agricultural Runoff and Private Wells." Working Paper 15-05, EPA National Center for Environmental Economics, Washington, DC.
- Halvorsen, R., and R. Palmquist. 1980. "The Interpretation of Dummy Variables in Semilogarithmic Equations." *American Economic Review* 70(3): 474–475.
- Harrington, D., G. Maddox, and R. Hicks. 2010. "Florida Springs Initiative Monitoring Network Report and Recognized Sources of Nitrate." FDEP, Tallahassee, FL. Available at www.dep.state.fl.us/springs/reports/files/springs_report_102110.pdf.
- Jackson, T.O. 2001. "The Effects of Environmental Contamination of Real Estate: A Literature Review." *Journal of Real Estate Literature* 9(2): 93–116.
- Johnson, B.B., and C. Chess. 2003. "How Reassuring Are Risk Comparisons to Pollution Standards and Emission Limits?" *Risk Analysis* 23(5): 999–1007.
- Kennedy, P. 1981. "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations." *American Economic Review* 71(4): 801.
- LeSage, J., and R.K. Pace. 2009. *Introduction to Spatial Econometrics*. Boca Raton, FL: Chapman & Hall / CRC Press.
- Malone, P., and R. Barrows. 1990. "Ground Water Pollution's Effects on Residential Property Values, Portage County, Wisconsin." *Journal of Soil and Water Conservation* 45(2): 346–348.
- Michael, H.J., K.J. Boyle, and R. Bouchard. 2000. "Does the Measurement of Environmental Quality Affect Implicit Prices Estimated from Hedonic Models?" *Land Economics* 76(2): 283–298.
- Netusil, N.R., M. Kincaid, and H. Chang. 2014. "Valuing Water Quality in Urban Watersheds: A Comparative Analysis of Johnson Creek, Oregon, and Burnt Bridge Creek, Washington." *Water Resources Research* 50(5): 4254–4268.
- Page, G.W., and H. Rabinowitz. 1993. "Groundwater Contamination: Its Effects on Property Values and Cities." *Journal of the American Planning Association* 59(4): 473–481.
- Poor, P.J., K.J. Boyle, L.O. Taylor, and R. Bouchard. 2001. "Objective versus Subjective Measures of Water Clarity in Hedonic Property Value Models." *Land Economics* 77(4): 482–493.
- Poor, P.J., K.L. Pessagno, and R.W. Paul. 2007. "Exploring the Hedonic Value of Ambient Water Quality: A Local Watershed-based Study." *Ecological Economics* 60(4): 797–806.
- Richards, B.K., S. Pacenka, A.E. Salvucci, S.M. Saia, L.F. Whitbeck, P.M. Furdyna, and T.S. Steenhuis. 2012. "Surveying Upstate New York Well Water for Pesticide Contamination: Cayuga and Orange Counties." *Groundwater Monitoring Review* 32(1): 73–82.

- Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *The Journal of Political Economy* 82(1): 34–55.
- Smith, K.V., W.H. Desvousges, F.R. Johnson, and A. Fisher. 1990. "Can Public Information Programs Affect Risk Perceptions?" *Journal of Policy Analysis and Management* 9(1): 41–59.
- Solo-Gabriele, H., D-M. Sakura-Lemessy, T. Townsend, B. Dubey, and J. Jambeck. 2003. "Quantities of Arsenic within the State of Florida." Report 03-06, State University System of Florida, Florida Center for Solid and Hazardous Waste Management, Gainesville, FL.
- Southern Regional Water Program. 2015. "Drinking Water and Human Health in Florida." SRWP, College Station, TX. Available at <http://srwqis.tamu.edu/florida/program-information/florida-target-themes/drinking-water-and-human-health>.
- Sudarshan, K., and K. Venkataraman. 2013. "Reconnaissance of Groundwater Quality Impact." *Water Environment Research* 85(10): 1700–1714.
- Van Garderen, K., and C. Shah. 2002. "Exact Interpretation of Dummy Variables in Semilogarithmic Equations." *Econometrics Journal* 5(1): 149–159.
- Walsh, P.J., and J.W. Milon. 2015. "Nutrient Standards, Water Quality Indicators, and Economic Benefits from Water Quality Regulations." *Environmental and Resource Economics*: 1–19.
- Walsh, P.J., J.W. Milon, and D.O. Scrogin. 2011. "The Spatial Extent of Water Quality Benefits in Urban Housing Markets." *Land Economics* 87(4): 628–644.