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What Do Property Values Really Tell Us?
A Hedonic Study of Underground Storage Tanks

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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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By: Dennis Guignet[1]

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Abstract:
Hedonic property value models are widely used, but are susceptible to omitted variable bias and potentially invalid conjectures regarding the assumed measure of environmental quality. This paper focuses on an application where both are of particular concern: leaking underground storage tanks. I estimate a hedonic model using quasi-experimental and spatial econometric techniques. Similar to previous studies, I examine how house prices vary with distance to the disamenity. This approach yields little evidence that prices are adversely impacted. However, to better measure risks, I utilize home-specific data on correspondence from environmental regulators, and find a 9-12% depreciation when households are well-informed.

JEL Classification: D63 (Externalities); I18 (Government Policy; Regulations; Public Health); Q51 (Valuation of Environmental Effects);

Keywords: hedonic analysis, housing prices, leaking underground storage tanks, LUST, contaminated sites, groundwater contamination, remediation benefits.

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[1] National Center for Environmental Economics; US Environmental Protection Agency; Mail Code 1809 T 1200 Pennsylvania Avenue, N.W.; Washington, DC 20460; guignet.dennis@epa.gov

I. Introduction

In the absence of markets for environmental quality, researchers rely on non-market valuation techniques to estimate the value of environmental amenities and disamenities. One of the most widely used revealed preference approaches is hedonic property value models, where the value of an environmental commodity is inferred from its impact on home prices. Hedonics is an attractive technique because housing transaction data is readily available, the method relies on actual market behavior, and it presumably captures all aspects of a change in welfare.

There are, however, two practical issues in obtaining valid welfare estimates. The first is omitted variable bias. If there are unobserved influences on house prices that are correlated with the assumed measure of environmental quality, then the implicit price estimates of interest may be biased. The second is whether the measure of environmental quality assumed in the hedonic model reflects what buyers and sellers in the market are actually aware of, and care about.[1] To address, or at the very least illustrate, these issues, I focus on an application where both are of particular concern: groundwater pollution from leaking underground storage tanks (LUSTs), such as those found at gas stations.

I estimate a hedonic property value model using a unique and comprehensive dataset of house transactions, neighborhood characteristics, underground storage tank (UST) facilities, leak investigations, and groundwater well contamination tests, for three Maryland counties (Baltimore, Frederick, and Baltimore City) from 1996-2007. Disentangling the implicit price of LUSTs and cleanups is challenging because the placement of UST facilities (and hence potential leaks) may be correlated with the spatial distribution of other amenities and disamenities. Moreover, the UST facilities themselves pose both desirable and undesirable characteristics besides contamination.

I take several steps to reduce potentially confounding effects on home values. I include (i) extensive controls in the hedonic regressions (home and neighborhood attributes), (ii) neighborhood fixed effects, and (iii) comparable non-leaking USTs. The latter, along with temporal variation in the discovery of leaks, allow for a spatial difference-in-difference regression framework (see Horsch and Lewis, 2009). I also implement a "propensity score" type of hedonic model, where in the first stage I estimate the probability that a leak is discovered at the individual UST facilities. This is then included in the right-hand side of the hedonic model, which essentially allows for a comparison of home values around leaking and non-leaking tanks that have a similar propensity for a leak to be discovered. Repeat sales and spatial econometric models are estimated to check the robustness of the results.

Previous hedonic property value studies often rely on proximity of a home to the disamenity and discrete informational events to proxy environmental quality (Boyle and Kiel, 2001; Farber, 1998). However, it remains unclear whether this is always a valid measure for environmental and health risks, especially in the context of LUSTs. A unique contribution of this paper is that in addition to measuring risk solely by proximity to the disamenity, I also account for home-specific variation in information and pollution, which I measure with domestic groundwater well tests and correspondence from the Maryland Department of Environment (MDE).

I ask four main research questions. First, analogous to the conventional identification strategy, is the value of houses in close proximity to a UST adversely impacted when a leak is discovered, and how does this change when cleanup is undertaken and completed? Second, does this effect differ depending on whether the primary exposure pathway (private groundwater wells) is present? Third, how are prices impacted at a subset of homes where households have additional information regarding the disamenity? Fourth, what are the implications for using hedonics in benefit-cost analysis?

Despite extensive efforts to control for potential omitted variable bias, in general, I find that the typical LUST has little effect on the price of surrounding homes (e.g., within 500 meters). This holds even if a home relies on a private well. Based solely on this conventional identification strategy of relying on distance, a researcher may conclude that home values are not impacted by LUST sites, and therefore that cleaning up or preventing these leaks yields no benefits (at least as capitalized in property values). However, I do find a significant 9-12% depreciation among homes where the private well was tested for contamination. These households face actual (or suspected) risks and are relatively well-informed since they receive correspondence from MDE.

This illustrates how hedonic analyses can lead to vastly different conclusions depending on the assumed measure of environmental quality, and brings into question findings from previous hedonic studies where more refined environmental measures were not available. More care is needed towards how we measure an environmental good in the right-hand side of our hedonic models. Particular attention should be given to what information buyers and sellers in the market have regarding the amenity or disamenity of interest, how they perceive this information, and how well our assumed environmental measure reflects these perceptions.

The rest of this paper is organized as follows. Section II reviews the hedonic literature relevant to this analysis. Section III provides background information on LUSTs. The empirical framework is outlined in section IV. I describe the data in section V, and present the results in section VI. Section VII concludes.

II. Previous Literature

II.A. The Hedonic Price Method

In a differentiated good market (e.g. housing) the matching of buyers and sellers forms a hedonic price schedule, where the price of the differentiated good is a function of the attributes composing that good. The marginal contribution of each attribute to the overall value of the good is the marginal implicit price. Rosen (1974) demonstrated that in equilibrium the marginal implicit price equates to the buyer's marginal willingness to pay, implying that marginal welfare estimates can be obtained with no information on people's underlying preferences, and that only the hedonic equation needs to be estimated.

To estimate non-marginal welfare changes one may have to pursue the second stage of Rosen's procedure, and estimate the underlying demand functions.[2] However, under certain assumptions non-marginal welfare impacts from sufficiently local disamenities (i.e. only affect a few homes so as not to shift the hedonic price function) are simply windfall gains or losses to the property owners, and therefore can be estimated solely from the hedonic price function (Palmquist, 2005). I make this assumption here since pollution from a LUST usually only migrates a few hundred meters, at most.

Hedonic models have been used extensively to value air quality and visibility (e.g. Chattopadhyay, 1999; Kim and Goldsmith, 2009), water quality (e.g. Leggett and Bockstael, 2000; Walsh et al., 2011), noise (e.g. Pope, 2008, Day et al., 2007) and health risks (e.g., Gayer et al., 2002; Davis, 2004), among other things. There are several areas of research that are particularly important to understanding the effects of LUSTs on home values.

II.B. Groundwater Quality and Residential Property Values

To my knowledge the few studies investigating the effects of groundwater contamination on residential property prices generally find little or no effect. For example, Malone and Barrows (1990) found that nitrates in the groundwater did not affect home prices. Examining seven different towns in Wisconsin, Page and Rabinowitz (1993) report that assessed values are not affected by well contamination from landfills, industrial sites, or pesticide run-off. Dotzour (1997) finds that groundwater pollution does not lead to a significant difference in the average house price in Wichita, Kansas, which is not surprising since most (if not all) of the homes were connected to the public water system. These studies provided valuable contributions, but are well over a decade old, and econometric techniques and data quality have improved greatly since that time.

More recently, Boyle et al. (2010) find that home prices decline by 0.5-1% for each 0.01 mg/l of arsenic above the 0.05 mg/l standard set by the EPA. This depreciation appears to be temporary since prices rebound within a few years. Boyle et al. speculate this may be due to the availability of in-home water treatment systems or dissipation of perceived risks once media attention stops.

II.C. Contaminated Sites and Residential Property Values

There is a significant literature on the effects of larger contaminated sites (e.g. Superfund sites) on home values. Often the identification strategy in these studies is to account for proximity to the site, and allow the implicit price of proximity to differ before and after a contamination-related event (e.g. discovery of contamination, listing on the National Priorities List, cleanup being undertaken, and cleanup completion).[3] Each event represents new information that may change public perceptions of environmental and health risks, and in turn, affect property values. The change in the premium for distance from a site reflects a change in residents' welfare.[4]

Kohlhase (1991) and Michaels and Smith (1990) are among the earliest to study the effects of contaminated sites on property values. Farber (1998) reviews these and subsequent hedonic studies and finds that property values increase, on average, by $3,500 for each additional mile from a contaminated site. However, Boyle and Kiel (2001) find significant variation across studies, ranging from $190 to $11,450 per mile. Most find that home prices decrease when a site is placed on the NPL (Kiel, 1995; Farber, 1998; Boyle and Kiel, 2001; Jackson, 2001), but Kiel and Williams (2007) find that this may not be the case at all sites.

Evidence that home values rebound during and after cleanup is mixed (Kiel and Zabel, 2001; Dale et al., 1999; McCluskey and Rausser, 2003; Kiel and Williams, 2007). Even though cleanup reduces objective risks, property values may not rebound because of a lingering social stigma (e.g., Messer et al, 2006; Gregory and Scatterfield, 2002). The site may still be perceived as a threat, and the surrounding community publicly shunned.

Overall, the mixed results from this literature suggests that there is significant heterogeneity across sites, and more refined measures of environmental quality are needed to control for such heterogeneity.

II.D. LUSTs and Residential Property Values

While there is a vast literature on how larger types of contaminated sites affect property values, comparability of these studies to LUSTs is unclear. LUSTs are more numerous, less publicized, relatively smaller in size, and pollution is more local. LUSTs are comparatively homogeneous in that contamination mainly consists of petroleum products, and the sites are generally gas stations, or similar types of commercial and industrial facilities. In contrast, Superfund and other contaminated sites are comprised of a wide assortment of prior land uses and pollutants. Most hedonic studies focusing on larger contaminated sites are concerned with just a single site or assume that only the nearest site affects property values, but there are numerous USTs and LUSTs within a single housing market.

There are few studies on LUSTs and residential property values. Simons et al. (1997) estimate a hedonic model using a cross-section of home sales in Cuyahoga County, Ohio, and find a 17% depreciation associated with homes within 300 feet of a leak at a registered UST facility. They find no effect associated with proximity to registered non-leaking tanks or non-registered LUSTs. In a later analysis, Simons et al.

(1999) find that "contamination" from nearby gas stations reduces home values by 14-16%.[5] Isakson and Ecker (2010) focus on 50 USTs in Cedar Falls, Iowa, which environmental regulators categorized as "no risk," "low risk," and "high risk." They find that the prices of homes adjacent to a high risk LUST are about 11% lower.

Due to the small sample size and cross-sectional nature of these studies, one should use caution when interpreting the results as causal. In contrast, I utilize a large panel of home sales over 11 years, which allows me to better identify the causal impact of LUSTs on property values. Using the same dataset, my study extends on an earlier analysis by Zabel and Guignet (2011), who emphasized the need to exploit both spatial *and* temporal variation in identifying the causal effects of LUSTs on home values.

Zabel and Guignet (2011) include neighborhood fixed effects and spatial econometric techniques to minimize potential biases from unobserved spatially correlated influences on house prices. Even more importantly, they observed home sales before and after the leak, allowing them to establish a pre-leak baseline, and analyze how prices change upon the discovery of a LUST, and completion of a leak investigation. They examined home prices within 100, 200, 500, 1000, and 2000 meters of a LUST, and checked whether the impact of a leak varied depending on the severity of contamination, the presence of an exposure pathway, and publicity surrounding the site.

In general, Zabel and Guignet (2011) found that the typical LUST had little effect on home values, but more publicized (and more contaminated) sites can cause more than a 10% depreciation at homes up to 1,000 meters away. Focusing on these sites individually, however, revealed substantial heterogeneity in the price impact, ranging from a 12% depreciation to a 14% appreciation. This again suggests the need for a more refined measure of environmental quality.

In this paper, I devise a quasi experiment focusing only on leaks at UST facilities registered with Maryland's Oil Control Program. In contrast, Zabel and Guignet (2011) focus on all LUSTs, including historical sites where regulators were previously unaware that an old inactive UST was (or had been) present. When focusing only on registered USTs a clear counterfactual exists, homes near non-leaking registered UST facilities. These can be compared to homes near leaking USTs, both before and after the leak. This framework allows me to estimate difference-in-difference and "propensity score" types of hedonic models. Additionally, in this paper a repeat sales model is estimated to check the robustness of the results.

A key contribution of this research is that, in contrast to previous hedonic analyses, I utilize home-specific variation in information and environmental quality, namely well tests and correspondence from environmental regulators.

II.E. How to Measure Risk

Despite its widespread use, it remains unclear whether distance to the source of pollution is always an acceptable proxy for environmental and health risks, especially in the context of LUSTs. First of all, if the general public is unaware of the pollution problem, then no threat is perceived and distance is unrelated to perceived risk. In this case, there would be no premium for distance of a home from the disamenity.

While people can see gas stations, and other UST facilities, it is unclear whether they are always aware of a LUST near their home. USTs are underground and there may be no obvious visual cues of contamination. When a leak does occur, there is little media attention, if any, and if there is, it is restricted to only the most severe cases.[6]

The Maryland Department of Environment (MDE) requires a responsible party (usually the UST owner) to notify the public only in the most severe cases, where a corrective action plan is necessary.[7] Notification is only required for "members of the public directly affected by the release and planned corrective action" (COMAR, 26.10.09.08). Under Maryland real estate disclosure laws, sellers are not required to disclose information about any nearby pollution unless the for-sale property is actually contaminated.

Additionally, simply looking at proximity to a LUST assumes that the spatial extent of the effect on property values is the same across all sites, and homogeneous in all directions, but this may not be true. The spread of contamination plumes are complicated by unobserved groundwater flows (Page and Rabinowitz, 1993). Cameron (2006) shows the importance of accounting for directional heterogeneity around a contaminated site and presents a method for doing so, but her approach is not applicable here because the effect of LUSTs on home values is too local and there are too few sales to statistically analyze individual sites.

Following the traditional approach in the hedonic literature, I examine the impact of proximity to a LUST on house prices, and how this varies across informational events (e.g. leak discovery, cleanup, and cleanup completion). In addition, I have compiled a unique dataset of private well contamination tests and correspondence from MDE, which allows me to identify households who are relatively well-informed and face actual (or suspected) risks. Well contamination levels are observed at the end of the complicated hydrogeological processes, and thus provide a measure of risk that already accounts for spatial heterogeneity of contamination around an individual LUST site, and across sites.

III. Background on Leaking Underground Storage Tanks

There are about 595,000 industrial and commercial facilities that store petroleum or other hazardous substances in underground tanks (US EPA, 2011d). Tanks could eventually leak as a result of corrosion, cracks, defective piping, or spills during refilling and maintenance. Leaking contaminants can seep into the soil and local groundwater. These pollutants may migrate to surrounding water bodies and ecological systems via surface run-off or groundwater flows.

Human health can be adversely affected by the consumption of contaminated groundwater, inhalation of vapors, and dermal contact with contaminants. Those most at risk are among the 15% of Americans who rely on private groundwater wells, which are not regulated by the Safe Drinking Water Act, and for which there are no testing, monitoring, and treatment requirements (US EPA, 2011c).The majority of the regulated USTs contain petroleum substances, the by-products of which include harmful compounds, such as benzene (a proven carcinogen), and toluene, ethyl benzene, and xylenes (commonly abbreviated as BTEX), which affect the kidneys, liver, and nervous system (US EPA, 2011b). Furthermore, motor fuel can contain harmful additives, such as Methyl tertiary butyl ether (MTBE), a former gasoline additive and suspected carcinogen (Toccalino, 2005; US EPA, 2011b).

Congress first mandated the US Environmental Protection Agency (EPA) establish a comprehensive program regulating USTs in 1984, by adding Subtitle I to the Resource Conservation and Recovery Act. Since then, the EPA has encouraged the States to develop their own UST programs, for which they can seek formal approval. In total, about 495,000 leaking underground storage tanks (LUSTs) have been identified throughout the United States. Cleanups have been initiated at 470,460 LUST sites, and completed at 401,874 sites (US EPA, 2011d), making the UST program perhaps the largest remediation program for which the EPA is responsible. For comparison, there are currently a total of 1,298 sites on the Federal National Priorities List (NPL) and 354 sites have been deleted (US EPA, 2011a).

With the cost of cleanup ranging from a few thousand to millions of dollars at each LUST site (US EPA, 2004; Khan et al., 2004), and given large number of sites, potential health risks, and extensive government involvement, it is useful and important to find out what the benefits of cleanup and prevention are.

IV. The Empirical Model

IV.A. A Difference-in-Difference Approach

Consider a single housing market. I posit that the price of home *i* in neighborhood *j* at period *t* (p_{ijt}) is a function of structural characteristics of the home (e.g. interior square footage) and its location, where the latter includes UST facilities and perceived environmental and health risks associated with that location. Formally,

$p_{ijt} = f(\boldsymbol{x}_{ijt}, \boldsymbol{UST}_{ijt}, \pi_{ijt})$, where $\boldsymbol{x}_{ijt}$ denotes home structure and neighborhood characteristics, $\boldsymbol{UST}_{ijt}$ is the presence (or number of) UST facilities in close proximity, and π_{ijt} denotes perceived environmental and health risks.

Risk perceptions are formed from a given information set about the disamenity and location: $\pi_{ijt} = \pi(\boldsymbol{UST}_{ijt}, \boldsymbol{LUST}_{ijt}, \boldsymbol{Test}_{it})$. The vector $\boldsymbol{LUST}_{ijt}$ denotes the presence of a leaking UST within a given distance of home *i* in each of the three stages of the contamination/cleanup process.

Briefly, based on MDE practice, if a leak is (i) *discovered* then an investigation is undertaken by the environmental regulators to assess the situation and determine the appropriate actions. MDE may require that (ii) *cleanup* be undertaken, which could include removal of the tank, excavation of contaminated soil, and the extraction and treatment of groundwater, among other things. Not all LUSTs undergo active cleanup efforts. Petroleum products naturally degrade over time, so if there is no public or environmental threat then ongoing monitoring and natural attenuation are sometimes deemed the best course of action (US EPA, 2004; Khan et al., 2004). If cleanup is undertaken, it is usually complete by the time the leak investigation enters the third and final stage, (iii) *closure* of the case, which is reached when the regulatory agency no longer considers the LUST a threat.

If buyers and sellers in the housing market are aware of a LUST and perceive it as a disamenity or risk to human health, then one would expect home prices to decrease upon the discovery of a leak, and to rebound back to pre-leak levels after cleanup. If these conditions do not hold, then property values may be unaffected. It is also possible that prices may not rebound after cleanup because the site may still be perceived as a threat, or because of a residual social stigma (Messer et al, 2006; Gregory and Scatterfield, 2002).

A unique aspect of this study is the inclusion of home-specific information regarding leaks and pollution in private groundwater wells, denoted $\boldsymbol{Test}_{it}$. If the Maryland Department of Environment (MDE) suspects that contamination has migrated into a private groundwater well, they will notify the residents, usually with a personal letter informing them about the LUST and requesting to test their well. After testing, MDE sends a follow-up letter with the test results and regulatory standards. If contamination is found, additional tests and notification letters may occur. This is not common to all homes near a LUST, thus the households whose wells are tested are relatively well informed about actual or potential risks.

I do not observe perceived risks directly and must therefore estimate a reduced-form hedonic model. Assuming a log-linear functional form, the model is

$$\ln p_{ijt} = \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{UST}_{ijt}\boldsymbol{\gamma} + \boldsymbol{LUST}_{ijt}\boldsymbol{\theta} + \boldsymbol{Test}_{it}\boldsymbol{\alpha} + v_j + \boldsymbol{M}_t + \varepsilon_{ijt} \qquad (1)$$

where v_j is a neighborhood specific fixed effect to control for all unobserved time-invariant neighborhood influences, $\boldsymbol{M}_t$ denotes quarterly and annual fixed effects to capture overall market trends, and ε_{ijt} is a disturbance term.[8] The coefficients to be estimated are $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\boldsymbol{\theta}$, and $\boldsymbol{\alpha}$.

$\boldsymbol{UST}_{ijt}$ includes all UST facilities, whether leaking or not. The coefficient $\boldsymbol{\gamma}$ captures the baseline effect of desirable and undesirable characteristics associated with these facilities and the surrounding area. This yields a clean quasi-experimental framework where the "treatment" is the discovery of a leak (denoted by $\boldsymbol{LUST}_{ijt}$). Home sales around registered USTs that never leak serve as a control, sales around LUSTs before the leak is discovered are the treated group before the treatment, and sales after a leak is discovered are the treated group after the treatment. This is similar to what Horsch and Lewis (2009) refer to as a spatial difference-in-difference approach.

Assuming that the unobserved characteristics captured by $\boldsymbol{\gamma}$ do not change over time in a manner correlated with LUST events, the elements of vector $\boldsymbol{\theta}$ are the causal effects of (i) a leak being discovered, (ii) contamination being cleaned up, and (iii) a leak case being closed, on the value of homes in close proximity. The coefficient $\boldsymbol{\alpha}$ is the additional impact of groundwater well testing and contamination on the value of a home.

IV.B. A Propensity Score Approach

In addition to OLS estimation of equation (1), I also pursue several variants of it. The first entails a two-stage control function or propensity score type of approach (Wooldridge, 2002, Chp. 18). This framework essentially compares the price of homes around leaking UST facilities to a control group of homes around non-leaking facilities that have similar propensities for a leak to be discovered. This approach may better control for confounding influences associated with a particular facility that are correlated with the discovery of a leak. For example, if larger UST facilities are more likely to leak, and larger facilities are more of a nuisance to residents, then we must properly control for such heterogeneity in the baseline in order to accurately estimate $\boldsymbol{\theta}$.

The “propensity score” approach is done in two steps. In the first step I estimate a probit model of the probability that a leak is discovered at each individual UST facility. Formally:

$$PS_k = Prob(leak_k) = \Phi(\boldsymbol{tank}_k \boldsymbol{\psi}) \quad (2)$$

where $leak_k$ is a dummy variable equal to one if a leak is discovered at UST facility *k*, and $\boldsymbol{tank}_k$ is a vector of characteristics of the facility (e.g., age, number of tanks, site use) and its location (e.g., hydrogeology, exposure pathway and receptors, neighborhood socio-demographics). $\boldsymbol{\psi}$ is a vector of unknown coefficients. I posit that the propensity that a leak is discovered follows a normal distribution, so $\Phi(\cdot)$ is a standard normal cumulative density function. A probit model is then estimated via the method of maximum likelihood.

The predicted propensity of a leak at each UST facility $\left(\widehat{PS}_k = \Phi\left(\boldsymbol{tank}_k \widehat{\boldsymbol{\psi}}\right)\right)$ is then used to derive the expected number of leaks around each home, formally

$$\widehat{leaks}_i = \sum_{k \in \Im_i} \widehat{PS}_k \quad (3)$$

where $\Im_i$ denotes the set of all UST facilities in close proximity to home *i* (e.g., 500 meters). In the second step, I add $\widehat{leaks}_i$ to equation (1), yielding:

$$\ln p_{ijt} = \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{UST}_{ijt}\gamma + \widehat{leaks}_i\varphi + \boldsymbol{LUST}_{ijt}\boldsymbol{\theta}$$

$$+\boldsymbol{Test}_{it}\boldsymbol{\alpha} + v_j + \boldsymbol{M}_t + \varepsilon_{ijt} \quad . \quad (4)$$

Similar to a propensity score model, in (4) I estimate the average treatment effect $\boldsymbol{\theta}$ (i.e., the effect of a LUST on home values) conditional on the propensity for "treatment." In theory, the estimated coefficient φ further accounts for the non-random discovery of a leak, or "treatment" assignment (Rosenbaum and Rubin, 1983).

IV.C. Repeat Sales and Spatial Autoregressive Models

The second variant of equation (1) is a repeat sales model, where unobserved time invariant characteristics associated with a home and its specific location are differenced out (Palmquist, 1982). Suppose home *i* was sold in some earlier period $s < t$, then the repeat sales model is:

$$\Delta \ln p_{ijts} = \Delta \boldsymbol{x}_{ijts}\boldsymbol{\beta} + \Delta \boldsymbol{UST}_{ijts}\boldsymbol{\gamma} + \Delta \boldsymbol{LUST}_{ijts}\boldsymbol{\theta}$$

$$+\Delta \boldsymbol{Test}_{its}\boldsymbol{\alpha} + \Delta \boldsymbol{M}_{ts} + \Delta \varepsilon_{ijts} \qquad (5)$$

where Δ denotes the change in value from period *s* to *t*. Both the repeat sales and neighborhood fixed effect models account for unobserved time invariant influences associated with a home and its location, but do not control for time-varying unobserved heterogeneity.

The third variant of (1) is a spatial autoregressive model (Anselin, 1988; LeSage and Pace, 2009), where a spatiotemporal lag of neighboring home sales is included in the right-hand side of the hedonic equation to soak up any local time-varying confounders. This lag is basically a weighted average of past home prices within some predefined neighborhood. The model is presented below in matrix notation,

$$\boldsymbol{P} = \rho \boldsymbol{W}_1 \boldsymbol{P} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{UST}\boldsymbol{\gamma} + \boldsymbol{LUST}\boldsymbol{\theta} + \boldsymbol{TEST}\boldsymbol{\alpha} + \boldsymbol{M} + \boldsymbol{\varepsilon} \qquad (6)$$

Let n denote the number of observed home sales, then $\boldsymbol{P}$ is a $n\times 1$ vector containing the natural log of the price for all sales, $\boldsymbol{W}_1$ is a row-standardized $n\times n$ spatial weight matrix defining the neighbor relations, and ρ is the spatial lag coefficient which is meant to absorb unobserved and potentially confounding characteristics associated with the location of a home. The model later estimated also accounts for spatial autocorrelation. In other words, in equation (6), $\boldsymbol{\varepsilon} = \boldsymbol{W}_2\boldsymbol{\varepsilon} + \boldsymbol{u}$, where $\boldsymbol{W}_2$ is a row-standardized $n\times n$ spatial weight matrix defining the relationship between neighboring disturbance terms, and $\boldsymbol{u}$ is a $n\times 1$ vector of *iid* error terms.

V. The Data

The empirical analysis focuses on single-family home sales from 1996-2007 in three Maryland Counties: Baltimore, Frederick, and Baltimore City (see figure 1). I focus on Maryland because a comprehensive dataset of home transactions was available, and I could physically access the leak investigation files at the Maryland Department of Environment (MDE). I selected these counties because they have a good mix of urban and rural areas, and homes served by public water versus private wells.[9] The four main components of the dataset are described below.

V.A. Underground Storage Tanks

The State of Maryland requires all tanks meeting certain criteria be registered with its Department of Environment (COMAR 26.10.02). MDE's Oil Control Program provided data on all registered USTs in Maryland. Attention is restricted to the 3,516 registered UST facilities in Baltimore (1495), Baltimore City (1562), and Frederick (459)

Counties.[10] Table 1 shows that the majority of UST facilities are in areas served by public water, but there are 426 USTs in areas where households rely on private groundwater wells. Among the 1,300 UST facilities where the use is listed, 574 (44.2%) are gas stations, 305 (23.5%) are classified as commercial, and 421 (32.4%) as industrial.[11] The average UST facility has three tanks and a total capacity of 17,363 gallons. Just over half (53.9%) of the facilities had no active tanks at the beginning of the study period. From 1996 to 2007 leaks were discovered at 138 (3.92%) of these registered UST facilities (see figure 2).

V.B. Leaking Underground Storage Tanks

MDE's Oil Control Program provided data on 42,100 petroleum "cases" in Maryland, which includes routine compliance checks, the opening and closing of USTs, and leak investigation and remediation cases. Out of these cases, 284 pertain to leak investigations for vapor intrusion, or soil and groundwater contamination, in the study area, and that were first opened between 1996 and 2007. Lesser cases where contamination was not found or was minimal and could not conceivably affect property prices were disregarded, leaving 255 cases. I disregard investigations that were not linked to a UST at a valid address, leaving 219 cases. To ensure a relatively homogeneous set of LUSTs and better control for pre-leak conditions I focus only on the 138 leak investigations that were undertaken at a registered UST facility.

The State of Maryland does maintain an electronic database of LUST cases, but much of the key information remains in hard copy files, which are available only at the MDE office in Baltimore. I spent over 200 hours reviewing and retrieving records from individual case files at MDE.

Gathering site-specific details turned out to be crucial to the analysis because despite the fact that LUSTs involve a relatively homogeneous class of pollutants (petroleum by-products), I find substantial heterogeneity in pollution severity, public knowledge, and investigation activities. Among the 138 LUST sites, 34 (24.6%) were in a private well area (see table 2). There was evidence confirming that contamination migrated to neighboring properties in just 27 cases (19.6%). As of the end of 2007, active cleanup efforts had been undertaken at 61 LUSTs (44.2%). Remediation technologies included soil excavation, pump-and-treat, vacuum extraction, soil vapor extraction, recovery sumps, containment walls, concrete caps, and bioremediation (e.g. oxygen and enzyme injections). Considering the 84 leak cases that were resolved by the end of 2008, the average was open for 1.79 years (median 1.24 years), the shortest was a day, and the longest was 10.48 years.

V.C. Home Sales

Data on single family homes come from Maryland Property View (MDPV) 1996-2007, which compiles the tax assessment databases maintained by the tax assessor's office in each county of the state. There are a total of 244,169 single-family homes with valid geographic coordinates: 59,671 in Frederick County, 152,488 in Baltimore County, and 32,015 in Baltimore City.[12] The hedonic analysis focuses on the 132,840 sales from 1996-2007 for this set of homes.[13] The average transaction rate per year is thus 4.53%. The median price over that period is $215,063 in Baltimore County, $279,627 in Frederick County, and $125,931 in Baltimore City (2007$).[14]

Descriptive statistics of the home characteristics are shown in table 3. MDPV contains geographic coordinates and several structural characteristics for each home (e.g., interior square footage, lot size, the number of bathrooms, etc.). I derived several locational variables using a Geographic Information System (GIS) and data from various sources.[15] I define neighborhoods according to the 2000 Census block groups for Baltimore and Frederick counties, and by census tract for Baltimore City.[16] This produces 498, 127, and 200 "neighborhoods," respectively. Other spatial attributes are included to control for local variation within a neighborhood (e.g., distances to major roads and public open space).

Distance from a home to surrounding USTs was calculated using GIS. The average sale is 718 meters from the nearest registered UST, and 2.2 km from the nearest LUST. There are 17,963 sales (13.5%) within 200m of a UST and 65,367 (49.2%) within 0-500m. Considering only these sales, there were 3.58 USTs within 500m of the average home sold. Almost half (48.2%) of all single-family homes (not just sales) are within 500m of a UST, confirming that USTs truly are ubiquitous.

Identification of the effect of LUSTs on property values requires that transactions occur during the various stages of the leak investigation/cleanup process. Table 4 shows the number of sales during each of these stages that are within 0-200 and 200-500 meters of the LUST. Notice there are relatively few sales, and thus few observations for statistical identification, in the more rural private well areas, which is where households face potentially higher risks.

V.D. Potable Well Contamination Tests

If MDE suspects a household's well has been contaminated by a leak, a letter is sent notifying the residents of the situation and requesting to test their well. MDE then sends the test results to the residents. If warranted, regularly scheduled testing and correspondence will continue.

During 1996-2007 there were over 7,700 potable well tests conducted at 670 different homes and businesses, 633 of which were single-family homes. Only 50 single-family home transactions took place after the well had been tested (18 in Baltimore and 32 in Frederick counties), corresponding to 11 different LUST cases. Often MDE found minimal contamination, if any, and it was therefore not necessary to continue testing. However, in some cases several testing events were warranted. At 16 homes only one well test was undertaken prior to the sale, but the well water at 34 homes was tested multiple times.[17]

If contamination is found at a residence to be sold, the prospective seller is required by law to disclose such information. Contamination was found at 23 of the 50 sales where testing occurred: BTEX in 11 domestic wells and MTBE in 19 (see table 5).[18] Ten home sales took place where pollution levels in the potable well exceeded regulatory standards. Granulated active carbon (GAC) filters, which essentially eliminate all pollutants, were installed and maintained by MDE for nine of these 10 home sales.

On average, the most recent MDE-conducted well test relative to the sale date was 1.55 years prior to the sale (the median is 124 days). At 32 (64%) of the tested homes, testing occurred both before and after the transaction, suggesting that sellers *and* buyers were aware of the LUST and groundwater contamination.

VI. Hedonic Regression Results

VI.A. Base Hedonic Model Results

In the first set of hedonic price regressions I estimate several variants of equation (1). The dependent variable is the natural log of the sale price (2007$). In table 6, I estimate a single hedonic price function for all three counties.[19] Since these counties could be considered separate housing markets, the estimated coefficients associated with attributes of the home and its location, as well as the year and quarter time effects, are allowed to vary across the counties. For now, however, I constrain the estimated price effects of a UST and leak and cleanup events to be the same across all counties.

Perceived pollution risks are measured by three dummy variables denoting that a LUST is within 500 meters, and is in one of the three stages: i) leak discovered, ii) cleanup, iii) post-closure.[20] The corresponding regression coefficients can be interpreted as a percent change in price relative to the pre-leak values. To absorb any unobserved confounding influences on prices, I include a dummy variable denoting whether a non-leaking UST, or a LUST that has not yet leaked, are within 500 meters. In a difference-in-difference framework, these dummies denote the "control" group of homes, and the "treated" group prior to treatment, respectively.

In model 6.A I do not include neighborhood fixed effects or other variables to control for unobserved effects on prices. This model serves as a baseline to compare with models where I better control for confounding influences and heterogeneity. Only the coefficient estimates of interest are shown, but the sign and significance of those not presented are as expected.[21] The -0.0201 coefficient on *non-leaking UST within 0-500m* suggests that homes near a UST sell for about 2% less. Homes near a UST that will eventually leak tend to sell for 7% less (as seen by *LUST within 500m*). Neither result should necessarily be interpreted as causal.

The 0.1126 coefficient on *leak discovered* suggests an 11% increase in property values when a leak is found and an investigation opened, which is against initial expectations. It is possible that the public is unaware of the discovery of a LUST, or does not perceive it as a threat, but this would imply no change in prices. This counterintuitive appreciation may be due to omitted variables associated with a home and its location, which I better account for in later regressions. As seen by *cleanup* and *post-closure*, model 6.A suggests a small and statistically insignificant price effect when cleanup is undertaken, and the investigation subsequently completed.

Model 6.B includes neighborhood fixed effects. Accounting for unobserved heterogeneity in this fashion does reduce the counterintuitive appreciation upon leak discovery by more than 50% (relative to model 6.A), suggesting that the neighborhood fixed effects may be absorbing some of the omitted variable bias. However, the discovery of a leak still seems to lead to an unexpected 4.77% increase in property values.

Leak discovery is well distributed both spatially and temporally, so the coefficient on *leak discovered* is unlikely to pick up unobserved effects due to a particular location or time period. This coefficient could, however, absorb unobserved effects that are systematically occurring at LUSTs in different locations and time periods in a manner correlated with leak discovery.

Anecdotally, at least eight of the leak investigations were opened because contamination was found during redevelopment. This is one potential explanation as to why leak discovery is associated with an increase in home values. Unfortunately, I could not identify a clear measure of redevelopment to include in the hedonic regressions.[22]

To better control for unobserved heterogeneity that may vary over time or within a neighborhood, in model 6.C I add the natural log of the median price of all single-family home sales within 500 meters of a home, and that took place within 3 years prior to the sale. Clearly this variable is endogenous, but I do not wish to make any inference about the resulting coefficient. It is included solely to absorb potentially confounding local (and possibly time varying) influences on home prices. This adds explanatory power, but does not change the LUST related coefficients.

Model 6.D is a repeat sales model. Following equation (5), the home and location specific time invariant characteristics are differenced out. The median neighbor price is included to help control for unobserved local trends. The estimated coefficient on *leak discovered* is much smaller, suggesting only a 1.6% appreciation, which is not statistically different from zero. Cleanup seems to have a small and insignificant effect on prices, but closure of a leak investigation leads to a marginally significant 4.4% depreciation, suggesting a residual perception of risk or public stigma after the environmental threat is eliminated. However, unless the residential housing market is simply slow to capitalize this stigma, one would also expect lower home values during the discovery and cleanup of a leak.

VI.B. Hedonic Results by County

In tables 7 through 9, I repeat the above regressions for each county individually. There are too few sales in close proximity to a LUST to estimate a separate repeat sales model for each county. Instead, spatial autoregressive and autocorrelation models are estimated following equation (6).[23] Again, only the coefficients of interest are displayed. Focusing first on Baltimore City (table 7), in the specifications controlling for unobserved neighborhood effects (models 7.B and 7.D) we see no significant effect of LUSTs on home prices.

The Baltimore County results (table 8) suggest that although the prices of homes within 500 meters of a UST and future LUST site tend to be lower, the discovery of a LUST, cleanup, and closure of a leak investigation have no adverse effect on prices. In fact, models 8.B through 8.D suggest a counterintuitive 5% appreciation in home prices upon the discovery of a leak. There is some evidence that home values appreciate 2.68% to 5.41% upon cleanup and closure of a leak investigation, relative to before the leak was discovered (see models 8.C and 8.D).

In Frederick County (table 9), the results suggest that the discovery of a LUST leads to a 2.53% to 4.68% increase in home prices, although this is only marginally significant in some specifications. There is some weak evidence that prices are slightly lower during the cleanup of a LUST site (but this is only marginally significant at best).

I next examine whether the baseline effects of USTs on home values vary according to the type of UST facility, and whether this affects the estimated LUST impacts. In the state of Maryland's database of registered USTs, facilities are classified as gas stations, commercial, industrial, or as “unknown” (which means that the use was not specified on the UST inspection report).

In table 10, for Baltimore City (model 10.A) we see some evidence that the baseline effect of proximity to a UST on home prices depends on the type of facility. For example, homes within 500 meters of a gas station are associated with 6% lower values, all else constant (although this effect is not statistically significant at the conventional levels, p-value = 0.11). On the other hand, among UST facilities where the use is not specified, prices tend to be 4% higher. Based on a Wald test, for Baltimore City I reject the null that the baseline price effects are equal across different types of UST facilities (p-value=0.0316). For Baltimore (model 10.B) and Frederick (model 10.C) counties, however, I fail to reject this null hypothesis, suggesting that different types of UST facilities are associated with similar effects on the price of homes within 500 meters.

Comparing the results in table 10 to those in tables 7 through 9, it appears that controlling for the baseline effects across different types of UST facilities does not affect the estimated impacts of the discovery of a leak, cleanup, and closure of a leak investigation. One exception is that model 10.A suggests that in Baltimore City, home prices decrease by 9.97% upon closure of a leak investigation, as opposed to the statistically insignificant 6.6% decline found when we do not distinguish between the type of UST facility (see model 7.C).

Focusing just on Baltimore and Frederick counties, in table 11 I examine whether the presence of an exposure pathway matters. Separate regressions are estimated for homes in private well areas versus those in areas connected to the public water system.

Again we see that leaks and related activities generally have a small and often insignificant effect on surrounding home prices.

Previous specifications sometimes revealed an unexpected appreciation in home values when a leak was discovered. The results here suggest that this primarily occurs to homes connected to the public water system, and hence where the primary exposure pathway to contamination is *not* present. As seen in model 11.A, the discovery of a LUST is associated with a 4.21% increase in price for homes connected to the public water system. Among homes that rely on private wells (model 11.B), however, leak discovery is associated with a statistically insignificant 2.95% appreciation in value.

In short, the analysis thus far suggests that, if anything, leak discovery is associated with an unexpected small, albeit statistically significant, increase in surrounding home values. However, this result does not hold across all specifications, and is most notably absent in the results focusing on homes that rely on private groundwater wells (which consists of households who are most at risk), and the repeat sales model (which one could argue best controls for omitted variables). In the next section I further examine this result using a more refined quasi-experimental framework.

VI.C. Hedonic Results from a Refined Quasi Experiment

In table 12 I focus only on homes within 500 meters of a registered UST, and as such, this hedonic model only compares homes near USTs where a leak did and did not occur. Model 12.A focuses on all three counties. This is a spatial difference-in-difference model comparing home sales around registered non-leaking USTs (the control group), to sales near LUST sites (treated group), both before and after the leak. The *LUST within*

500m dummy is included to account for any "pre-treatment" price differences between the control and treated groups. The fact that this coefficient estimate is statistically insignificant, lends support to the selection of the control group. Even in this refined model, the only significant result is an unexpected 4.64% appreciation upon the discovery of a leak. A similar result holds even when focusing on homes with private wells (model 12.C).

An alternative two-step "propensity score" type of model, as shown in equations (2)-(4), is estimated for models 12.B and 12.D. Since the treatment (i.e., the discovery of a leak) is "assigned" to USTs, and not homes per se, I estimate the discovery of a leak at a UST facility (see equation 2). The binary dependent variable equals one if a leak is discovered at a UST facility from 1996-2007 (n=138), and zero otherwise (n=3,378). Several probit models of leak discovery are estimated and discussed in the appendix.

I use the estimated coefficients from the first stage probit model to estimate the probability (or propensity) of leak discovery at each UST facility. The mean predicted probability of a leak among non-leaking USTs is 3.49% (median=1.28%), compared to 14.39% (median=12.9%) among the 138 LUSTs.[24] Figure 3 displays the distribution of predicted propensities, and shows that the common support is fairly wide (0.0037 to 0.7198).

I next calculate the predicted number of leaks near each home by summing up the predicted leak probability for all USTs within 500 meters (see equation 3). The hedonic model (equation 4) is then estimated. In table 12, model 12.B focuses on all homes within 500 meters of a UST. As seen by the coefficient on the *Propensity Score* variable, each additional predicted LUST site is associated with a 5.3% decline in home prices. Caution is warranted in interpreting this as a causal effect, but this does suggest that even conditional on a nearby UST facility, “treatment” is not necessarily random. Nonetheless, the inclusion of the “propensity score” does not significantly change the estimated effects of a LUST on home prices. We still see small and statistically insignificant impacts, except for the 4.03% appreciation upon the discovery of a leak. The results are similar when focusing just on homes that rely on private wells (model 12.D).[25]

Despite extensive efforts to reduce potentially confounding influences, I find no robust evidence that prices are adversely impacted by a nearby LUST. Perhaps potential buyers and sellers of homes that are merely in close proximity to the disamenity do not perceive it as a threat, or are completely unaware of it. In the last set of regressions I examine an alternative measure of the disamenity, where I *know* households are relatively well-informed and face actual or suspected risks.

VI.D. Hedonic Results with Well Tests

The regressions in table 13 focus only on homes in private well areas, and include a dummy denoting whether the well water at individual homes was tested prior to a sale (*Well Tested*). Model 13.A considers all homes that rely on private wells. The significant coefficient on *Well Tested* suggests that the price of tested homes decreases by 11.36%. Models 13.B and 13.C focuses only on the sale of homes that are most at risk (those that rely on private wells and are within 500 meters of a UST); both models suggest a 10.85% and a 11.37% depreciation, respectively.

There are only 50 sales where MDE tested the well prior to the transaction. Despite this small number of observations the results suggest a fairly large and statistically significant depreciation. To make sure these dummies are not just picking up unobserved heterogeneity associated with this subset of homes, in table 14 I add a dummy denoting observations where a transaction took place before the well was tested (*Sold before Well Test*). All else constant, if sales where well testing occurred prior to the sale are similar to those where testing occurred later, then this dummy controls for any unobserved heterogeneity associated with this subset of homes. There is little change in the *Well Tested* coefficient, and in fact, the inclusion of this control bolsters the result. I calculate the impact as:

$$Well\ Test\ Impact = \{\exp(\alpha_{\text{Well Tested}} - \alpha_{\text{Sold before Well Test}}) - 1\} \qquad (7)$$

and find an 11% to 12% depreciation in these cases where the households are relatively well-informed about the LUST and groundwater pollution, and face actual (or potential) risks.

Although the results are not reported here, in subsequent analysis I found that if a test shows pollution levels above the regulatory standard, then prices decrease about 14%, but this is not statistically different from the 10% depreciation among homes where the tests revealed no contamination, or levels below the standard.

VII. Conclusion

The goal of this paper was to illustrate two practical issues with hedonic property value models using an empirical application to groundwater pollution from leaking underground storage tanks (LUSTs). Omitted variable bias and the validity of the assumed environmental measure are of particular concern in this context. Disentangling the implicit price of LUSTs, and hence inferring welfare impacts, is challenging because LUSTs are relatively unpublicized pollution events, and the spatial distribution of UST facilities and leaks, may be correlated with other confounding influences on property values.

Focusing on three Maryland counties (Baltimore, Frederick, and Baltimore City) from 1996-2007, I conducted a detailed hedonic study on house prices. I control for a large set of home and neighborhood attributes in the hedonic regressions, including neighborhood fixed effects. To further reduce omitted variable bias, I implement difference-in-difference and "propensity score" approaches by accounting for leaking and non-leaking tanks, and exploiting the temporal and spatial variation in the discovery of leaks. As a robustness check, repeat sales and spatial autoregressive models are estimated.

Hedonic models examining home values around Superfund sites and other undesirable land uses generally rely on distance to the site and contamination related events to measure the magnitude of the disamenity (see Boyle and Kiel, 2001; Farber, 1998). Following this approach, I find that homes simply near a LUST (e.g., 500 meters) do not typically decline in value upon the discovery of a leak, even when an obvious exposure pathway is present (private groundwater wells). Similarly, there is no clear evidence that prices respond to cleanup and closure of a leak investigation. Based solely on this typical identification strategy, a researcher may conclude that LUSTs do not impact home values, and therefore that there is little benefit to preventing and cleaning up these leaks (at least as reflected in home values).

However, in this application, and perhaps others, it remains unclear whether distance is always the best proxy measure for environmental quality. Residents who are merely living near a LUST may not always perceive it as a threat, or may not even be aware of it.

A unique aspect of this paper is that I incorporate an alternative environmental measure that captures home-specific variation in information and pollution, namely domestic groundwater well test results from the Maryland Department of Environment (MDE). Households whose wells were tested are relatively well-informed because they receive correspondence from MDE. The mere testing of a private well by MDE signals to a household that there is suspected contamination, and perhaps even health risks. Furthermore, the test results may reveal that the private well is in fact contaminated.

Among these tested homes I find a 9-12% decline in value, which reflects a real welfare loss to these well-informed households. This result may also be partially capturing heterogeneity in pollution severity across LUST sites, because testing is more likely to take place at more severe sites. In either case, this illustrates the importance of properly selecting a valid measure of environmental quality for hedonic property value models, and brings into question the findings of past hedonic studies where more attention to the assumed environmental measure may be warranted.

Hedonic property value models are a useful non-market valuation tool that can be used to value a variety of environmental goods. However, in future applications we must be more cognizant of the assumed measure of these goods, and pay particular attention towards what information buyers and sellers in the real estate market possess, how they perceive this information, and how well our assumed environmental measure reflects these perceptions.

Appendix: Probit Models of the Discovery of a Leak at a UST Facility

This appendix presents the estimation results from the first step of a two-step "propensity score" type of hedonic framework discussed in section IV.B. Following equation (2), a probit model of the probability a leak is discovered at an individual UST facility is estimated. The binary dependent variable equals one if a leak is discovered at a UST facility between 1996 and 2007 (n=138), and zero otherwise (n=3,378).

The parameters in the probit model are estimated via the method of maximum likelihood. The estimated average marginal effects are displayed in table A1. Model A1.A includes characteristics of the UST system and facility, county dummies, and a dummy denoting the presence of the primary exposure pathway (*Private Well Area*). The results suggest that a leak is 7.9% more likely to occur, and be discovered, at a gas station. Leaks are discovered more often among larger facilities with more USTs (as seen by *# tanks at facility*).

A leak is 2.86% more likely to be discovered among UST facilities in the private well area, where the primary exposure pathway to the surrounding population is present and where USTs are more extensively regulated and monitored. In model A1.B, the positive coefficient on *# homes in 500m w/ Pvt Well* suggests that in the presence of an exposure pathway, the larger the potentially exposed population, the more likely a leak will be discovered (although this effect is not statistically significant at conventional levels). Finally, I find that leaks are less likely to be discovered when the groundwater aquifer is relatively deep below the surface. In models A1.C and A1.D I include census block group characteristics, which statistically speaking are not associated with the probability that a leak is discovered.

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Figures and Tables

Figure 1. Three Maryland Counties in Study Area.

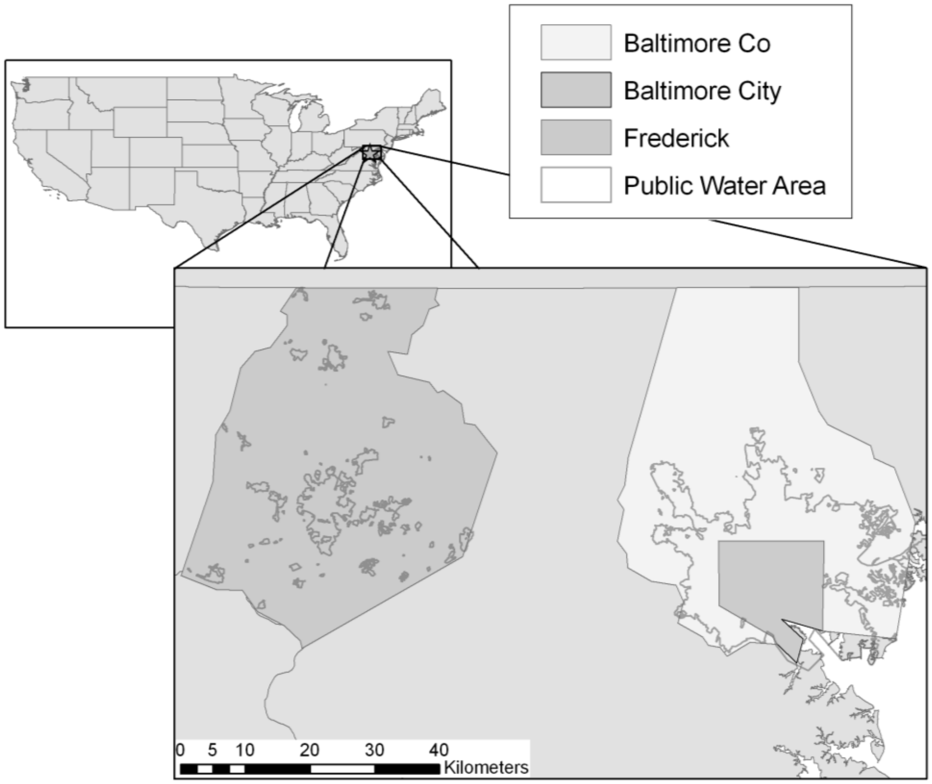


Figure 2. Registered Underground Storage Tanks and Leaks.

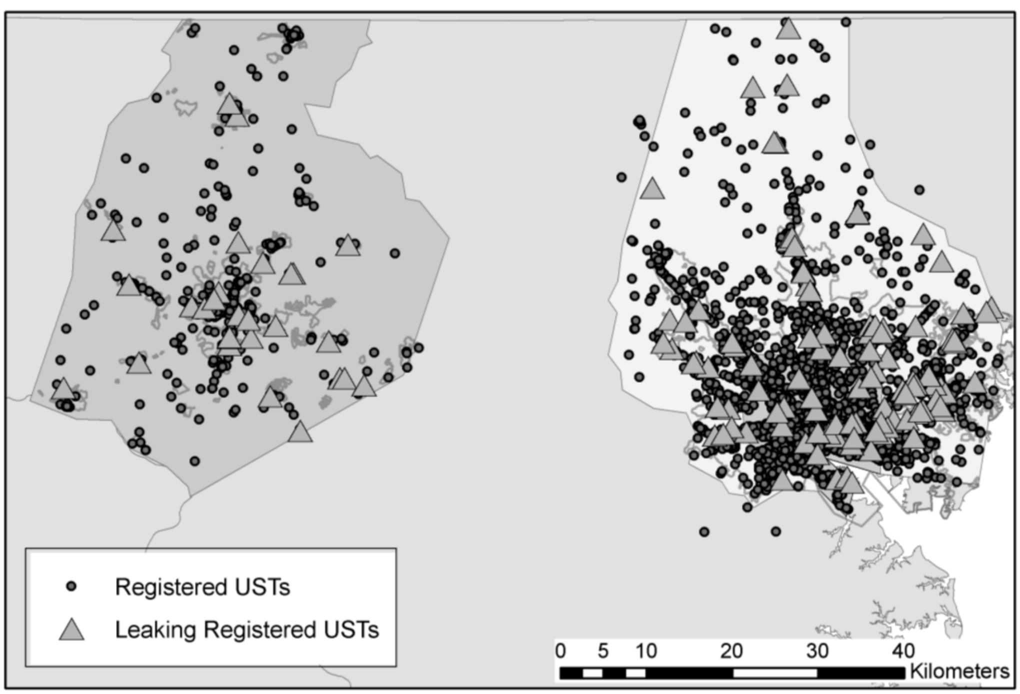
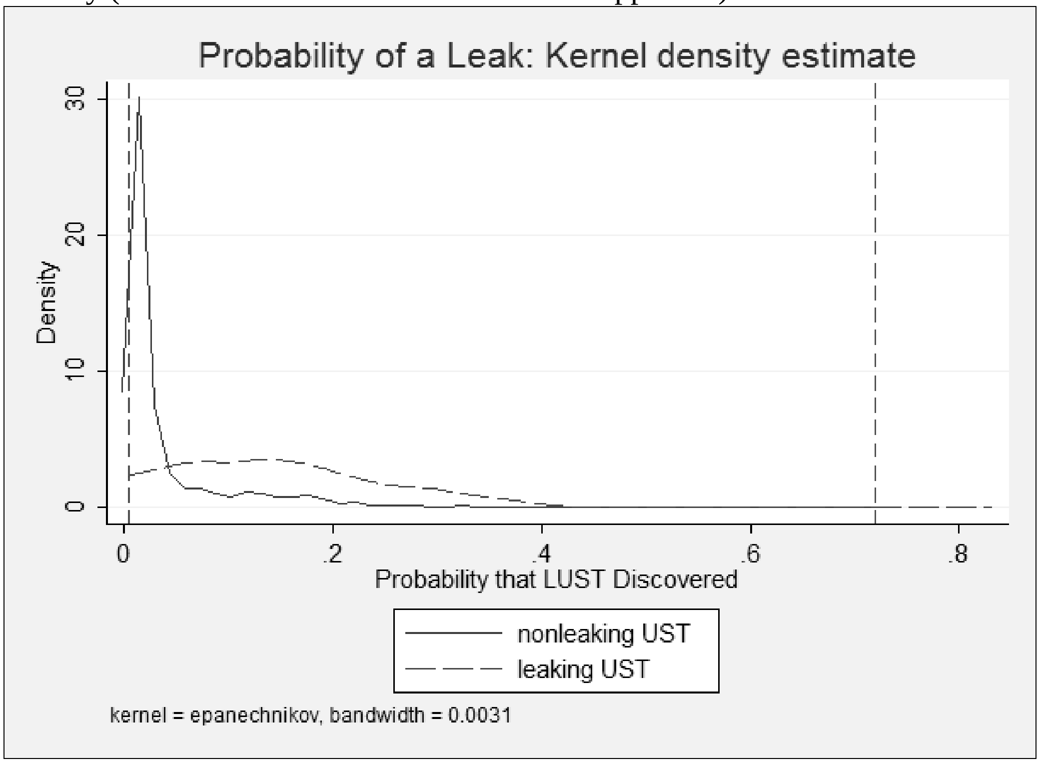


Figure 3. Kernel Density Estimate of the Probability that a Leak is Discovered at a UST Facility (from Model A1.B in Table A1 of the appendix).



Note: Gray dashed lines denote common support.

Table 1. Number of Registered Underground Storage Tank Facilities by County and Water Source.

County:	Public Water Area	Private Well Area	Total
Baltimore City	1,562	-	1,562
Baltimore	1,228	267	1,495
Frederick	300	159	459
Total	3,090	426	3,516

Table 2. Number of Leak Cases at Registered UST Facilities by Water Area.

	Public Water Area	Private Well Area	Total
Baltimore City	32	-	32
Baltimore	58	18	76
Frederick	14	16	30
Total	104	34	138

Table 3. Attributes of Single Family Home Sales in Baltimore City, Frederick, and Baltimore Counties.

Variable	Obs	Mean	Std. Dev.	Min	Max
price of home (2007$)	132840	263877	174084	15000	1979828
interior square footage	132840	1816.56	811.37	104	7976
lot size (acres)	132840	0.4424	0.6260	0.002	5
number full baths	132840	1.7445	0.7319	1	10
number half baths	132840	0.5279	0.5473	0	10
porch size (sqft)	123402	256.11	226.88	0	4260
number of fireplaces	103165	0.7489	0.6377	0	40
basement (dummy)	132840	0.8168	0.3868	0	1
number of stories	132840	1.6479	0.4630	1	4
attached garage (dummy)	132840	0.3602	0.4801	0	1
low quality construction[a]	132840	0.0043	0.0654	0	1
average quality construction[a]	132840	0.8016	0.3988	0	1
good quality construction[a]	132840	0.1871	0.3900	0	1
high quality construction[a]	132840	0.0042	0.0647	0	1
age of home (years)	132840	39.5311	30.1462	1	207
in private groundwater well area (dummy)	132840	0.1799	0.3841	0	1
distance to central business district (kilometers)[b]	132840	13.37	6.88	0.178	49.79
median home price in neighborhood (2007$)[c]	129688	235472	141029	1	6401731
meters to nearest public open space (meters)	132840	817	1086	0	10744
distance to nearest commercial zone (meters)	132840	671	723	0	9697
distance to nearest major road (meters)	132840	989	1089	0	10496

a. Dummy variables based on classification by tax assessors.
b. Central business district defined as Baltimore’s inner harbor for Baltimore County and City, and the City
of Frederick for Frederick County.
c. Median sales price over last 3 years, for all single-family homes within 500 meters of sale.

Table 4. Number of Sales During LUST Investigation and Cleanup Events.

LUST Stage	Entire Area	Entire Area (repeat sales)	Baltimore	Frederick	Baltimore City	Pvt Well Area
			0 - 200 meters			
Leak Discovery	216	63	111	59	46	33
Cleanup	98	18	53	41	4	7
Post-Closure	381	63	226	21	134	11
			200 - 500 meters			
Leak Discovery	1097	327	567	260	270	103
Cleanup	518	94	326	175	17	19
Post-Closure	2241	360	1166	110	965	74

Table 5. Private Well Contamination Levels Prior to Sale (n=23 sales with contamination).

	# Wells	**Last Test Mean Level (ppb)**		**Max Mean Level (ppb)**	
	Contaminated	Mean	Median	Mean	Median
BTEX	11	22.53	0	748	45
MTBE	19	213.70	0.49	252.92	18.90

Table 6. Base Hedonic Price Regression Results for Entire Study Area (Baltimore City, Frederick, and Baltimore County).

VARIABLES	Model 6.A ln(price)	Model 6.B ln(price)	Model 6.C ln(price)	Model 6.D[a] Δ ln(price)
Non-leaking UST within 500m (dummy)	-0.0201**	-0.0067*	-0.0033	
	(0.008)	(0.004)	(0.004)	
LUST within 500m (dummy)	-0.0724***	-0.0234**	-0.0186*	
	(0.026)	(0.011)	(0.010)	
× leak discovered (dummy)	0.1126***	0.0477***	0.0488***	0.0162
	(0.020)	(0.012)	(0.012)	(0.019)
× cleanup (dummy)	-0.0061	-0.0051	-0.0035	-0.0140
	(0.030)	(0.017)	(0.016)	(0.029)
× post-closure (dummy)	0.0136	0.0046	0.0063	-0.0439*
	(0.038)	(0.014)	(0.013)	(0.025)
Neighborhood Characteristics:				
ln(Median Neighbor Price)			0.1762***	0.1475***
			(0.013)	(0.017)
Neighborhood Fixed Effects	No	Yes	Yes	No
(Number of Fixed Effects)		(729)	(729)	
Repeat Sales Model	No	No	No	Yes
Home Characteristics:				
Home Structure × County	Yes	Yes	Yes	Yes
Home Location × County	Yes	Yes	Yes	No
Year and Quarter Dummies × County	Yes	Yes	Yes	Yes
Observations	132,831	132,831	132,831	27,128
R-squared	0.770	0.628	0.635	0.224

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

Note: Std errors are in parentheses. Errors are clustered by neighborhood group. (Neighborhoods are defined by census block groups for Baltimore and Frederick Counties, and census tract for Baltimore City).

a. Repeat Sales Model.

Table 7. Base Hedonic Price Regression Results for Baltimore City.

VARIABLES	Model 7.A ln(price)	Model 7.B ln(price)	Model 7.C ln(price)	Model 7.D ln(price)
Non-leaking UST within 500m (dummy)	0.0337	0.0168	0.0091	0.0374**
	(0.029)	(0.017)	(0.014)	(0.019)
LUST within 500m (dummy)	0.4682***	0.0738*	0.0726*	0.0397
	(0.097)	(0.041)	(0.040)	(0.053)
× leak discovered (dummy)	-0.2110*	0.0169	0.0120	0.0270
	(0.119)	(0.045)	(0.047)	(0.056)
× cleanup (dummy)	0.0076	-0.0075	-0.0012	0.0407
	(0.159)	(0.094)	(0.096)	(0.182)
× post-closure (dummy)	-0.5053***	-0.0641	-0.0666	-0.0585
	(0.105)	(0.044)	(0.043)	(0.061)
Neighborhood Characteristics:				
ln(Median Neighbor Price)			0.1780***	
			(0.032)	
Spatial Lag				0.0198***
				(0.003)
Spatial Autocorrelation				0.7915***
				(0.008)
Census Tract Fixed Effects	No	Yes	Yes	No
(Number of Tracts Effects)		(127)	(127)	
Home Characteristics:				
Home Structure	Yes	Yes	Yes	Yes
Home Location	Yes	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes	Yes
Observations	22,508	22,508	22,508	22,508
R-squared	0.539	0.338	0.347	
Log Likelihood				-13,788.01

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

Note: Std errors are in parentheses. Errors are clustered by census tract, except in model 7.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Table 8. Base Hedonic Price Regression Results for Baltimore County.

VARIABLES	Model 8.A ln(price)	Model 8.B ln(price)	Model 8.C ln(price)	Model 8.D ln(price)
Non-leaking UST within 500m (dummy)	-0.0269***	-0.0125***	-0.0076*	-0.0152***
	(0.009)	(0.004)	(0.004)	(0.0003)
LUST within 500m (dummy)	-0.1413***	-0.0552***	-0.0495***	-0.0911***
	(0.029)	(0.017)	(0.015)	(0.011)
× leak discovered (dummy)	0.1095***	0.0565***	0.0577***	0.0546***
	(0.024)	(0.016)	(0.014)	(0.013)
× cleanup (dummy)	0.0419	0.0092	0.0082	0.0334**
	(0.043)	(0.024)	(0.022)	(0.015)
× post-closure (dummy)	0.0650*	0.0248	0.0268*	0.0541***
	(0.037)	(0.017)	(0.015)	(0.011)
Neighborhood Characteristics:				
ln(Median Neighbor Price)			0.2017***	
			(0.012)	
Spatial Lag				0.0025***
				(0.000)
Spatial Autocorrelation				0.6821***
				(0.004)
Block Group Fixed Effects	No	Yes	Yes	No
(Number of Fixed Effects)		(479)	(479)	
Home Characteristics:				
Home Structure	Yes	Yes	Yes	Yes
Home Location	Yes	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes	Yes
Observations	75,881	75,881	75,881	75,881
R-squared	0.792	0.693	0.701	
Log Likelihood				-6,686.333

*** p<0.01, ** p<0.05, * p<0.1
Note: Std errors are in parentheses. Errors are clustered by census block group, except in model 8.D, where a nonzero correlation is allowed for the 7 nearest neighbors.

Table 9. Base Hedonic Price Regression Results for Frederick County.

VARIABLES	Model 9.A ln(price)	Model 9.B ln(price)	Model 9.C ln(price)	Model 9.D ln(price)
Non-leaking UST within 500m (dummy)	-0.0050	-0.0033	0.0023	-0.0013***
	(0.010)	(0.005)	(0.005)	(0.000)
LUST within 500m (dummy)	0.0011	-0.0021	0.0031	0.0019
	(0.024)	(0.010)	(0.010)	(0.002)
× leak discovered (dummy)	0.0545**	0.0253*	0.0274*	0.0468***
	(0.027)	(0.015)	(0.016)	(0.011)
× cleanup (dummy)	-0.0686**	-0.0140	-0.0101	-0.0323*
	(0.031)	(0.017)	(0.019)	(0.018)
× post-closure (dummy)	0.0372	-0.0134	-0.0076	-0.0048
	(0.045)	(0.025)	(0.022)	(0.019)
Neighborhood Characteristics:				
ln(Median Neighbor Price)			0.1362***	
			(0.013)	
Spatial Lag				0.0013***
				(0.000)
Spatial Autocorrelation				0.7604***
				(0.007)
Block Group Fixed Effects	No	Yes	Yes	No
(Number of Fixed Effects)		(123)	(123)	
Home Characteristics:				
Home Structure	Yes	Yes	Yes	Yes
Home Location	Yes	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes	Yes
Observations	34,442	34,442	34,442	34,451
R-squared	0.878	0.863	0.867	
Log Likelihood				-18,568.87

*** p<0.01, ** p<0.05, * p<0.1
Note: Std errors are in parentheses. Errors are clustered by census block group, except in model 9.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Table 10. Hedonic Price Results: Varying Baseline Effects by Type of UST Facility.

VARIABLES	Baltimore City Model 10.A	Baltimore County Model 10.B	Frederick County Model 10.C
UST within 500m (dummy)			
× gas station	-0.0626	-0.0141	-0.0026
	(0.039)	(0.009)	(0.008)
× commercial	0.0328	-0.0183	0.0029
	(0.025)	(0.014)	(0.013)
× industrial	-0.0221	-0.0212**	-0.0088
	(0.081)	(0.011)	(0.009)
× unknown	0.0434**	-0.0001	0.0042
	(0.019)	(0.006)	(0.005)
LUST within 500m (dummy)	0.1111***	-0.0353**	0.0018
	(0.038)	(0.015)	(0.012)
× leak discovered (dummy)	-0.0158	0.0549***	0.0295*
	(0.054)	(0.014)	(0.016)
× cleanup (dummy)	-0.0045	0.0077	-0.0055
	(0.102)	(0.021)	(0.020)
× post-closure (dummy)	-0.0997**	0.0199	-0.0088
	(0.040)	(0.016)	(0.022)
Neighborhood Characteristics:			
ln(Median Neighbor Price)	0.1766***	0.2023***	0.1363***
	(0.032)	(0.012)	(0.013)
Neighborhood Fixed Effects	Yes	Yes	Yes
(Number of Fixed Effects)	(127)	(479)	(123)
Home Characteristics:			
Home Structure	Yes	Yes	Yes
Home Location	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes
Observations	22,508	75,881	34,442
R-squared	0.348	0.701	0.867

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

Note: Std errors are in parentheses. Errors are clustered by neighborhood group. (Neighborhoods are defined by census block groups for Baltimore and Frederick counties, and census tract for Baltimore City).

Table 11. Hedonic Price Results for Private Well v. Public Water Areas (Baltimore and Frederick Counties).

VARIABLES	Public Water Area Model 11.A	Private Well Area Model 11.B
Non-leaking UST within 500m (dummy)	-0.0040	0.0048
	(0.004)	(0.006)
LUST within 500m (dummy)	-0.0317***	0.0102
	(0.012)	(0.016)
× leak discovered (dummy)	0.0421***	0.0295
	(0.012)	(0.020)
× cleanup (dummy)	0.0096	0.0271
	(0.016)	(0.038)
× post-closure (dummy)	0.0157	-0.0228
	(0.012)	(0.023)
Neighborhood Characteristics:		
ln(Median Neighbor Price)	0.2450***	0.1180***
	(0.014)	(0.009)
Neighborhood Fixed Effects	Yes	Yes
(Number of Fixed Effects)	(527)	(227)
Home Characteristics:		
Home Structure × County	Yes	Yes
Home Location × County	Yes	Yes
Year and Quarter Dummies × County	Yes	Yes
Observations	86,433	23,890
R-squared	0.722	0.786

*** p<0.01, ** p<0.05, * p<0.1
Note: Std errors are in parentheses. Errors are clustered by census block group.

Table 12. Quasi-Experimental Hedonic Results for Homes within 500 meters of UST.

	All Counties		Private Well Area	
VARIABLES	Model 12.A	Model 12.B	Model 12.C	Model 12.D
# of USTs within 0-500 m	-0.0010	-0.0005	0.0070	0.0079
	(0.001)	(0.001)	(0.005)	(0.005)
"Propensity Score" (pred. # leaks 0-500m)†		-0.0530**		-0.0051
		(0.027)		(0.056)
LUST within 500m (dummy)	-0.0118		0.0320	
	(0.011)		(0.023)	
× leak discovered (dummy)	0.0464***	0.0403***	0.0398**	0.0549***
	(0.011)	(0.010)	(0.019)	(0.020)
× cleanup (dummy)	0.0001	-0.0074	-0.0238	-0.0043
	(0.016)	(0.014)	(0.054)	(0.056)
× post-closure (dummy)	-0.0005	-0.0105	-0.0422	-0.0154
	(0.013)	(0.009)	(0.027)	(0.019)
Neighborhood Characteristics:				
ln(Median Neighbor Price)	0.1972***	0.1967***	0.1003***	0.1009***
	(0.022)	(0.022)	(0.022)	(0.022)
Neighborhood Fixed Effects	Yes	Yes	Yes	Yes
(Number of Fixed Effects)	(670)	(670)	(176)	(176)
Home Characteristics:				
Home Structure	Yes	Yes	Yes	Yes
× County	Yes	Yes	No	No
Home Location	Yes	Yes	Yes	Yes
× County	Yes	Yes	No	No
Year and Quarter Dummies × County	Yes	Yes	Yes	Yes
Observations	65,367	65,367	5,252	5,252
R-squared	0.547	0.547	0.786	0.786

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

Note: Std errors are in parentheses. Errors are clustered by neighborhood. (Neighborhoods are defined by census block groups for Baltimore and Frederick Counties, and census tract for Baltimore City).

† Standard Errors for predicted number of leaks are not adjusted to account for two-step procedure (see section VI.B).

Table 13. Hedonic Price Results with Private Well Testing (only homes in private well areas).

	All Homes	Within 500m of UST	
VARIABLES (dep variable = ln(price))	Model 13.A	Model 13.B	Model 13.C
# of USTs within 0-500 m	0.0088**	0.0074	0.0082*
	(0.004)	(0.005)	(0.005)
"Propensity Score" (pred. # leaks 0-500m)†			-0.0049
			(0.055)
Non-leaking UST within 500m (dummy)	-0.0063		
	(0.008)		
LUST within 500m (dummy)	-0.0078	0.0269	
	(0.015)	(0.023)	
× leak discovered (dummy)	0.0449**	0.0617***	0.0754***
	(0.019)	(0.020)	(0.021)
× cleanup (dummy)	0.0389	0.0018	0.0193
	(0.041)	(0.054)	(0.053)
× post-closure (dummy)	-0.0191	-0.0280	-0.0050
	(0.023)	(0.027)	(0.017)
Well Tested	-0.1136***	-0.1085**	-0.1137***
	(0.031)	(0.042)	(0.041)
Neighborhood Characteristics:			
ln(Median Neighbor Price)	0.1180***	0.0998***	0.1003***
	(0.009)	(0.022)	(0.022)
Neighborhood Fixed Effects	Yes	Yes	Yes
(Number of Fixed Effects)	(227)	(176)	(176)
Home Characteristics:			
Home Structure	Yes	Yes	Yes
× County	Yes	No	No
Home Location	Yes	Yes	Yes
× County	Yes	No	No
Year and Quarter Dummies × County	Yes	Yes	Yes
Observations	23,890	5,252	5,252
R-squared	0.786	0.787	0.787

*** p<0.01, ** p<0.05, * p<0.1
Note: Std errors are in parentheses. Errors are clustered by census block group.
† Standard Errors for predicted number of leaks are not adjusted to account for two-step procedure (see section VI.C).

Table 14. Hedonic Price Results with Private Well Tests: A Robustness Check (only homes in private well areas).

	All Homes	Within 500m of UST	
VARIABLES	Model 14.A	Model 14.B	Model 14.C
# of USTs within 0-500 m	0.0084*	0.0064	0.0072
	(0.005)	(0.005)	(0.005)
"Propensity Score"			-0.0177
(pred. # leaks 0-500m)†			(0.058)
Non-leaking UST within 500m	-0.0059		
(dummy)	(0.008)		
LUST within 500m (dummy)	-0.0099	0.0222	
	(0.016)	(0.025)	
× leak discovered (dummy)	0.0453**	0.0624***	0.0753***
	(0.019)	(0.020)	(0.021)
× cleanup (dummy)	0.0410	0.0052	0.0189
	(0.041)	(0.053)	(0.052)
× post-closure (dummy)	-0.0163	-0.0231	-0.0034
	(0.025)	(0.029)	(0.017)
Sold before Well Test	0.0112	0.0287	0.0354
	(0.019)	(0.025)	(0.025)
Well Tested	-0.1112***	-0.0963**	-0.0974**
	(0.031)	(0.041)	(0.041)
Neighborhood Characteristics:			
ln(Median Neighbor Price)	0.1179***	0.0998***	0.1003***
	(0.009)	(0.022)	(0.022)
Neighborhood Fixed Effects	Yes	Yes	Yes
(Number of Fixed Effects)	(227)	(176)	(176)
Home Characteristics:			
Home Structure	Yes	Yes	Yes
× County	Yes	No	No
Home Location	Yes	Yes	Yes
× County	Yes	No	No
Year and Quarter Dummies × County	Yes	Yes	Yes
Well Testing Impact	-0.1152***	-0.1175***	-0.1244***
	(0.033)	(0.043)	(0.041)
Observations	23,890	5,252	5,252
R-squared	0.786	0.787	0.787

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

Appendix Tables

Table A1. Probit of Leak Discovery at UST Facility, Estimated Average Marginal Effects (all 3,516 registered facilities in study area).

VARIABLES	Model A1.A	Model A1.B	Model A1.C	Model A1.D
Facility Characteristics:				
Industrial Facility (dummy)	-0.003288	-0.003745	-0.003613	-0.004006
	(0.0080)	(0.0075)	(0.0076)	(0.0074)
Gas Station (dummy)	0.079332***	0.079571***	0.079326***	0.078071***
	(0.0160)	(0.0160)	(0.0159)	(0.0156)
Facility Age	-0.000188	-0.000211	-0.000217	-0.000218
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
age missing (dummy)	-0.009141	-0.009566	-0.009705	-0.009827
	(0.0066)	(0.0062)	(0.0062)	(0.0061)
Facility built after 1996 (dummy)	0.001162	-0.000250	-0.000281	-0.000061
	(0.0132)	(0.0121)	(0.0120)	(0.0120)
Active USTs (dummy)	-0.001801	-0.001738	-0.001765	-0.001777
	(0.0043)	(0.0041)	(0.0041)	(0.0041)
# tanks at facility	0.003096***	0.002949***	0.002960***	0.002945***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
# previous leaks w/in 500m	0.002641	0.002228	0.002208	0.002349
	(0.0028)	(0.0027)	(0.0027)	(0.0026)
Location Characteristics:				
Baltimore County (dummy)	0.017067***	0.015266***	0.014088**	0.014514**
	(0.0057)	(0.0056)	(0.0063)	(0.0077)
Frederick County (dummy)	0.024674***	0.024656***	0.022970**	0.023189**
	-0.0111	(0.0112)	(0.0115)	(0.0135)
Private Well Area (dummy)	0.028553***	0.018831**	0.016669**	0.013952*
	(0.0101)	(0.0098)	(0.0100)	(0.0092)
# homes in 500m w/ Pvt Well		0.000097	0.000100*	0.000106*
		(0.0001)	(0.0001)	(0.0001)
Depth to groundwater (meters)		-0.000364**	-0.000372**	-0.000335*
		(0.0002)	(0.0002)	(0.0002)
Block Group Characteristics:				
median home value ($1000s)			0.000019	
			(0.0000)	
% pop in poverty				-0.006715
				(0.0324)
% housing vacant				0.026298
				(0.0378)
% housing own occupied				0.013834
				(0.0136)
Log Likelihood	-463.366110	-459.292861	-459.196168	-458.358468

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

[1] In the context of contaminated sites, these and other issues with hedonic property value methods are reviewed by US EPA (2011e, chapters 6 and 9).

[2] As first presented by Brown and Rosen (1982) and further discussed by Epple (1987), among others, this second stage procedure generally lacks proper identification because buyers simultaneously choose implicit prices when choosing a housing bundle. Two approaches have arisen to circumvent this identification problem (see Bockstael and McConnell, Ch. 6, pg 177). First, one can make specific functional form assumptions that imply identification mathematically. Second, analyzing several markets at once introduces proper instruments into the hedonic price function. In essence, analyzing several markets allows us to observe the "same" households' choices when facing different price schedules, thus tracing out the underlying bid functions. In contrast, Ekeland et al. (2004) argue that identification of the bid and offer functions can be obtained by using data within a single market by relying on differences in the curvature of the hedonic price, and bid and offer functions.

[3] The National Priorities List (NPL) is the list of Superfund sites which have been assessed to be the most harmful and are therefore inline for, or in the process of, remediation through CERCLA (US EPA, 2011a).

[4] Some researchers have gone beyond this approach and explicitly model risk perceptions, and how perceptions update with new information. Focusing on a Superfund site in Grand Rapids, MI, Gayer et al. (2000, 2002) infer a value per statistical cancer case avoided of $3.9-8.3 million. Similarly, Davis (2004) estimates the value to avoid a statistical case of pediatric leukemia to be $3-9.2 million.

[5] Simons et al. (1999) define contamination based on a 3 point scale, where 1= well test confirmed contamination at the home, 2= home is adjacent and down-gradient from a LUST, and 3= home is adjacent to a '1' or '2', down-gradient, and within 50-100 ft of the contamination plume. Only 11 contaminated homes were sold which is too few for a conventional hedonic analysis. Instead they compare the actual sales price to the predicted price from a hedonic regression that did not explicitly account for LUSTs.

[6] A Lexis Nexis and Google search for local news articles from 1997-2008 on LUSTs in Maryland uncovered 19 articles covering only 10 LUST sites. For comparison there are 138 LUSTs just in the three Maryland counties considered in this paper. Search keywords included combinations of "Maryland," "gas station," "leaking," "underground," "tank," "UST," "oil," "leak," and "LUST."

[7] At more severe LUST sites the responsible party may be required to submit a corrective action plan, which must provide adequate protection for human health and the environment (COMAR 26.10.09.07).

[8] I later assume ε_{ijt} is normally distributed, and allow for correlation at different levels of spatial aggregation, including clustering at the census block group or tract level, and more formal spatial autocorrelation models (see LeSage and Pace, 2009).

[9] According to the 1990 census, virtually all homes in Baltimore City are served by the public water system, and in Frederick and Baltimore Counties 43% and 8% of the homes use private wells, respectively, and the rest are mainly connected to the public water system.

[10] I disregard UST facilities that are i) classified as farms, residences, or government facilities, ii) relatively small tanks that are not regulated by MDE, or iii) missing a valid street address.

[11] Facility uses are as of May, 2009, and come from the Maryland Department of Environment's inspection reports.

[12] By home I mean a unique tax identification number that existed at least one year during the study period and corresponds to a single-family home.

[13] I restrict attention to arms' length sales, and exclude home sales with a price less than $15,000 (2007$) or greater than $2 million, a lot size greater than 5 acres or listed as zero, more than 10 full baths or 10 half baths, no full baths listed, and interior square footage listed as zero.

[14] Prices were converted to 2007 dollars using the National Consumer Price Index developed by the US Dept of Labor's Bureau of Labor Statistics (ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt, accessed Nov. 12, 2010).

[15] Data sources included the Baltimore County Department of Public Works, Frederick County Division of Planning, the Maryland Department of Planning, Maryland Department of Natural Resources, Federal Highway Administration, United States Geological Survey, and Maryland Geological Survey.

[16] Block groups in Baltimore City are relatively small and there are not enough single family-home sales to include block group fixed effects, therefore tract level fixed effects are used instead.

[17] Six homes had 2 tests prior the sale, seven homes had 3-5 tests, 11 homes had 6-20 tests, and 10 homes had 21-60 tests.

[18] BTEX is the summation of four commonly cited petroleum contaminants, all of which are individually regulated by the EPA under the Safe Drinking Water Act. The Maximum Contaminant Levels (MCL) are 5 parts per billion (ppb) for benzene, 100 ppb for toluene, 700 ppb for ethyl benzene, and 10,000 ppb for xylenes. MTBE is a former gasoline additive and suspected carcinogen. The regulatory threshold for MTBE in Maryland is 20 ppb, which is based on the EPA's taste and odor health advisory of 20-40 ppb in drinking water.

[19] Instead of a log-linear relationship, I enter the natural log of interior square footage and lot size as explanatory variables in the hedonic regressions. A quadratic term for age is also included. Values for a few attributes are missing from some observations, in which case these are coded to zero and a companion missing value dummy is included. More specifically, 29,675 (22%) sales were missing the number of fireplaces, 9,428 (7%) sales were missing porch square footage, and 376 (less than 0.5%) were missing a construction quality classification.

[20] The results are robust to the use of other distance buffers including 100, 200, 500, and 1,000 meters. The estimates are not reported here. See Zabel and Guignet (2010) for a more thorough examination.

[21] Full results are provided by Guignet (2011, pg 77-85).

[22] In earlier drafts I attempted to instrument for leak discovery, which in theory would eliminate confounding effects such as redevelopment. An instrument was constructed by estimating the probability that a leak is discovered at a UST in a given year, as a function of characteristics of the facility, tank system, geology, and the 2005 adoption of stricter UST regulations in groundwater sensitive areas in Maryland (COMAR, 26.10.02.03). This constructed instrument was then used in a two stage least squares procedure. Unfortunately the approach did not prove fruitful, possibly because the predicted probability that a leak is discovered in a given time period is extremely low, and due to the lack of time-varying instruments.

[23] Spatial autoregressive models were estimated in R using the "spdep" package (Bivand, 2010; R Development Core Team, 2010).

[24] These estimates are from the preferred specification (model A1.B in the appendix). The predicted propensities, and subsequent hedonic results, do not change substantially when the other specifications in table A1are used.

[25] Typically, in a propensity score regression framework the second stage standard errors are biased downward because they do not account for the sampling variation in the first stage parameter estimates. Although the standard errors can be adjusted via asymptotic formulas or by bootstrapping the first stage (Wooldridge, 2002, pg 614; Petrin and Train, 2003), such adjustments in this application are complicated by the fact that several UST facilities can be linked to a single home sale. Since the coefficient estimate corresponding to the predicted number of leaks is generally statistically insignificant, and its inclusion does

not significantly change the estimated implicit price of the discovery of a leak and cleanup activities, I do not attempt such adjustments here.