ABSTRACT

Title of Document: **WHAT DO PROPERTY VALUES REALLY TELL US? EVIDENCE FROM REVEALED AND STATED PREFERENCE STUDIES.**

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In the absence of markets for environmental quality, researchers resort to stated and revealed preference techniques to estimate the benefits of environmental programs. 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. There are, however, two practical issues in obtaining valid welfare estimates. The first is omitted variable bias, where the estimated impacts are confounded by omitted characteristics of the housing bundle. The second is whether the measure of environmental quality assumed in the hedonic models is the one that buyers and sellers in the market are aware of, and care about.

Stated preference approaches offer an opportunity to examine and, in some cases, circumvent these issues. I present three studies exploring the use of hedonic and stated preference methods in estimating the impacts of environmental disamenities on home values. The first study is an extensive hedonic analysis of

leaking underground storage tanks (LUSTs). I construct a quasi experiment and implement several econometric techniques to address omitted variable bias, paying special attention to alternative environmental quality measures.

I then present two stated preference studies, where the disamenities are conveyed using clearly specified quantitative measures. The first study focuses on LUSTs and groundwater pollution, which is expressed as parts-per-billion of benzene. This reflects the actual information given to households in the hedonic study. The second stated preference study asks respondents to choose among hypothetical homes, which vary in terms of price and mortality risks associated with local air pollution.

In my hedonic application I find that LUSTs generally have little effect on home values. I argue that this is because people typically do not have much information regarding this disamenity. This conjecture is confirmed by the significant depreciation at homes where households are well informed, as well as in the stated preference studies, where respondents are informed as part of the study design. While hedonics is a useful non-market valuation tool, in some applications pursuing both approaches may help us more accurately estimate the benefits of environmental programs.

WHAT DO PROPERTY VALUES REALLY TELL US?
EVIDENCE FROM REVEALED AND STATED PREFERENCE STUDIES

By

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Dedication

To my family,

for always being there and encouraging me to move forward.

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[1]Any opinions expressed throughout this dissertation are solely my own and do not necessarily reflect those of the US Environmental Protection Agency, the National Center for Smart Growth, the Maryland Department of Environment, or Fondazione Eni Enrico Mattei.

Table of Contents

List of Tables

Chapter 2: What Do Property Values Really Tell Us? A Hedonic Study of Pollution from Underground Storage Tanks.

Chapter 3: The Impacts of Pollution, Exposure Pathways, and Health Risks on Home Values: A Stated Preference Analysis.

Chapter 4: Can Property Values Capture Changes in Environmental Quality? Evidence from a Stated Preference Study in Italy and the UK.

List of Figures

Chapter 2: What Do Property Values Really Tell Us? A Hedonic Study of Pollution from Underground Storage Tanks.

Chapter 3: The Impacts of Pollution, Exposure Pathways, and Health Risks on Home Values: A Stated Preference Analysis.

Chapter 4: Can Property Values Capture Changes in Environmental Quality? Evidence from a Stated Preference Study in Italy and the UK.

Chapter 1: An Introduction

To what level should we regulate and clean up pollution? Economists recommend that the benefits of an environmental regulation or cleanup program be compared with the costs. It is, however, often difficult to estimate the benefits of preventing and remediating pollution. In many cases a large portion of these benefits stems from goods and services (e.g., health risks, ecological services) that are not traded in markets, and so we cannot directly infer their values.

In the absence of markets for environmental goods and human health risks, researchers resort to stated and revealed preference techniques for placing a value on these goods. Stated preference approaches directly elicit peoples' values from responses to hypothetical situations posed in a questionnaire. Revealed preference methods infer the value of an environmental amenity or disamenity indirectly by observing actual behaviors or related markets.

One of the most attractive and widely used revealed preference approaches is hedonic property value models, which posit that the price of a differentiated good, such as a home, is a function of the attributes of that good, including environmental quality. We infer peoples' values towards environmental goods by analyzing the prices of market goods that are at least partially characterized by the environmental commodity of interest. In the context of housing, the price of a home (or a monotonic transformation of it) is regressed on characteristics of the home, its location, and the surrounding environment. Rosen (1974) first laid the theoretical framework showing that marginal welfare estimates can be obtained solely from the hedonic price function, and no information on people's underlying preferences is needed.

Furthermore, for sufficiently localized goods, even non-marginal welfare impacts can be estimated directly from the hedonic price function (Palmquist, 2005).

Hedonic property value models have been applied to various environmental amenities and disamenities, including air quality and visibility (Chattopadhyay, 1999; Kim and Goldsmith, 2009), water quality (Leggett and Bockstael, 2000; Walsh et al., 2011), open space (Bell and Bockstael, 2000; Cho et al., 2009), noise (Pope, 2008, Day et al., 2007), land contamination and cleanup (Kiel and Williams, 2007), and health risks (Gayer et al., 2000, 2002; Davis, 2004). The widespread use of hedonic models is at least partially due to the increasing availability of property transaction data, advances in quasi-experimental and spatial econometric techniques, and developments in geographic information systems (GIS), which allow us to link property transactions to environmental goods of interest.

In general, hedonic approaches are viewed favorably because they rely on actual transactions in a marketplace. Studies often focus on housing markets because they are generally active, have lots of participants, and allow researchers to infer welfare effects on households (who are often the population most affected by a shift in environmental quality). There are, however, two practical issues in obtaining valid welfare estimates from the econometric models. The first is omitted variable bias. If the environmental amenity or disamenity is correlated with other omitted characteristics of a home or neighborhood, then the estimated marginal implicit prices may end up capturing the latter's effects on property values.

Second, researchers typically make assumptions regarding the public's awareness of the environmental good being studied, and how the buyers and sellers in the housing market measure this good. Such assumptions are often necessary, but rarely tested, and if proven invalid we may in fact be incorrectly inferring welfare effects from changes in property values.

Stated preference methods offer an opportunity to circumvent these issues. First, in a hypothetical questionnaire researchers can design a clean experiment that eliminates confounding influences. Second, people respond to valuation questions using the information and measure of environmental quality specified by the researcher. Therefore, we *know* people are aware of the environmental good being studied, and evaluate it using the same measure specified in the econometric models (assuming that the measures are clear to respondents). These advantages stem from the fact that stated preference surveys are hypothetical, which is the main criticism against the approach (Freeman, 1993, pg. 176).

In this dissertation I explore the use of hedonic property value and stated preference methods for measuring the effects of environmental disamenities on house prices, and ultimately towards estimating the benefits of environmental programs that prevent and clean up pollution. In chapter 2, I present an extensive hedonic property value study examining how a relatively understudied environmental disamenity, leaking underground storage tanks (LUSTs), affects house prices and transaction rates.

There are over 495,000 identified LUST sites (e.g., gas stations) across the United States (US EPA, 2011). Petroleum and other hazardous substances from these LUSTs can adversely affect the health of local residents, especially those who rely on private groundwater wells for their drinking water. I focus on three Maryland counties (Baltimore, Frederick, and Baltimore City), for which I compiled a unique and comprehensive dataset of homes and transactions, neighborhood characteristics, UST facilities, leak investigations, and groundwater well contamination tests, from 1996-2007.

I pay particular attention to (i) addressing omitted variable bias from unobserved neighborhood characteristics, and to (ii) alternative measures of environmental quality, and home buyers and sellers' awareness of these measures. To address the former, I include an extensive set of home and neighborhood attributes in the right-hand side of the hedonic model, including neighborhood fixed effects. I incorporate a quasi-experimental framework that compares homes near leaking and non-leaking tanks, and exploits the temporal and spatial variation in the discovery of LUSTs. Repeat sales and spatial autoregressive models are also estimated.

Typically, hedonic property value studies measure an environmental disamenity by a home's proximity to it (Boyle and Kiel, 2001; Farber, 1998), and examine how the implicit price of proximity varies across contamination and cleanup events. These events represent new information, which may change home buyers and sellers' perceptions of the disamenity; in theory, any resulting welfare shifts should be reflected in the change in the premium for distance from the disamenity. However, in my hedonic application it is unclear whether home buyers and sellers are always aware of a LUST and the cleanup events at the site.

A unique aspect of my study is that I account for home-specific variation in information and pollution, which I measure with domestic groundwater well tests and correspondence from environmental regulators. For this subset of homes, I do not need to assume that households are aware of the disamenity: I *know* they are. In fact, only among these tested homes do I find evidence of a decline in value (9-12%). I conclude the chapter by discussing the feasibility of a nationwide benefits study of the Underground Storage Tank (UST) program via hedonics versus alternative stated preference approaches.

Framing stated preference studies in the context of home values seems like a natural step to facilitate cross-method comparisons. However there are only a few stated preference studies on environmental goods and home values (Earnhart, 2001, 2002; Jenkins-Smith et al., 2002; Chattopadhyay et al., 2005; Simons and Winson-Geideman, 2005; Phaneuf et al., 2010). All of these studies convey the level of environmental quality in qualitative terms. For example, Chattopadhyay et al. (2005) present respondents with four different pollution scenarios (additional pollution, no change, partial clean-up, and full clean-up). Phaneuf et al. (2010) take a similar approach, and also vary the distance of a hypothetical home from the disamenity. While these measures may be relatively comparable to previous hedonic property value studies, I believe it remains unclear how survey respondents (and home buyers and sellers in the actual market) interpret such qualitative descriptions of changes in environmental quality.

In chapters 3 and 4, I present two stated preference studies that examine how pollution affects home values when the disamenity is conveyed using quantitative measures that are clearly specified to the respondents, namely (i) pollutant concentrations and (ii) objective health risks. Chapter 3 is a stated preference study where I examine how people believe home values are affected by leaking underground storage tanks and groundwater pollution. I convey the severity of pollution as X parts-per-billion of benzene in the groundwater. Corresponding with the hedonic analysis in chapter 2, the information presented to respondents mimics that sent to households whose private wells were actually tested for LUST contamination.

The survey was self-administered by a convenience sample of Maryland residents. My interests lie in making within sample comparisons across several randomly assigned treatments, namely hypothetical pollution levels at a home, and whether an exposure pathway is present. In general, I find that stated home prices decrease 18% to 24% due to a LUST, even when the groundwater beneath the home is not contaminated and an exposure pathway is not present. The respondents in this sample believe that the higher the levels of contamination, the larger the loss in home values, an effect that is more pronounced once the regulatory standard is exceeded, and is strongest when an exposure pathway, and thus health risks, are present.

Chapter 4 presents a stated preference study where I ask respondents to choose among hypothetical variants of their home, which vary in terms of price and the *mortality risks* associated with local air pollution levels. To my knowledge this is the first stated preference study to examine respondents' Willingness to Pay (WTP) for properties using a quantitative and clearly specified measure of health risks (e.g., an X in 1,000 probability of dying). The survey was implemented on a representative sample of residents aged 40-60 in Italy and the United Kingdom.

From the results I infer a Value of a Statistical Life (VSL) of about €1.828 to €5.775 million euro ($2.422 to $7.653 million USD), which varies across countries and depending on whether the respondents own or rent their home.[2] I find heterogeneity in respondents' WTP for a mortality risk reduction depending on socio-economic characteristics, and beliefs and perceptions regarding their local air pollution levels and the associated health risks.

Chapter 5 concludes, comparing the strengths and weaknesses of hedonic property value and stated preference approaches in estimating the benefits of environmental programs. In my hedonic application I find LUSTs generally have little effect on local home values. I believe that home buyers and sellers (at least in these Maryland counties) are typically unaware of this disamenity. In contrast, I do find a significant depreciation at homes where I know buyers and sellers are well informed, as well as in the stated preference studies, where respondents are explicitly informed as part of the study design. In some cases, pursuing both approaches will help economists better characterize how environmental quality affects property values, and in turn, more accurately estimate the benefits of environmental programs.

[2] Converted to US dollars using 0.75464 exchange rate, which was the average for the year 2010 (http://www.oanda.com/currency/average, accessed May 31, 2011).

Chapter 2: What Do Property Values Really Tell Us? A Hedonic Study of Pollution from Underground Storage Tanks

By: Dennis Guignet

I. Introduction

Over the last 30 years there has been considerable interest in, and controversy about, the US Environmental Protection Agency's (EPA) cleanup programs, such as Superfund and the Underground Storage Tank Program. There are several studies that suggest that these programs do yield benefits (see Farber, 1998; Boyle and Kiel, 2001), but whether they pass a benefit-cost analysis at the national level has been brought into question (e.g., Greenstone and Gallagher, 2008). In this paper I focus on the benefits of one of these cleanup programs, the Underground Storage Tank (UST) Program, and the use of hedonic property value methods to estimate the nationwide benefits of preventing and cleaning up leaks.

Congress first mandated the EPA to establish a comprehensive program regulating USTs in 1984. Since then about 495,000 leaking underground storage tanks (LUSTs) have been identified, and over 470,450 cleanups have been undertaken (US EPA, 2011), making it perhaps the largest remediation programs for which this agency is responsible.

There are currently about 600,000 industrial and commercial facilities that store petroleum or other hazardous substances in underground tanks (US EPA, 2011). Tanks may leak as a result of corrosion, cracks, defective piping, or spills during refilling and maintenance. I focus on petroleum pollution, which can harm human health and the environment. For people, the greatest potential threat is contamination of groundwater (US EPA, 2011).

The benefits of preventing or cleaning up a leak at a UST are mainly experienced by the residents in close proximity (i.e., a few hundred meters). Gas stations and other UST facilities are numerous and widespread, and so are leaks, which suggests that the aggregate benefits of the UST program may be large. However, to my knowledge there has been little research to estimate just how large these benefits might be.[3]

There are three main approaches to estimate the benefits of the UST program. The first is the damage function approach, where one estimates the reduction in risks to human health and ecological systems due to the prevention or cleanup of a LUST, and then assigns a value to this reduction based on past studies or policy. The drawback, however, is that the required risk information is site-specific, and notably absent from the Agency documents I examine in this study, as well as related studies.[4]

The second approach is a stated preference study, where one elicits benefit estimates from what survey respondents' state they would do in a hypothetical situation. An advantage of this approach is that the researcher can specify a scenario to elicit many aspects of the benefits of the UST program, including reduced human health and ecological risks, improved aesthetics, etc. Actual site-specific details are

[3] Exceptions include Simons et al. (1997, 1999), Simons and Winson-Geideman (2005), and Zabel and Guignet (2011). These studies examine how one (or a few) LUST site(s) affect local home values (see section III.D).

[4] For example, to my knowledge there are no epidemiological studies specifically on petroleum contamination from LUSTs, nor attempts to extrapolate risk assessment findings for individual contaminants to a state or national scale. Vrijheid (2000) reviews over 50 epidemiological studies on residents surrounding contaminated sites, but in all of these studies petroleum was only one of many contaminants, so the health risks posed by just petroleum pollution could not be identified.

not necessary since stated preference surveys are hypothetical. The primary criticism against this technique is that what people say in a hypothetical situation may not reflect their true actions (Freeman, 1993, pg. 176).

A third approach, which is the one pursued here, is the hedonic property value model. Hedonics is an attractive technique for estimating the benefits of preventing and cleaning up leaks because it relies on actual market behavior, and presumably captures all aspects of the benefits.

If buyers and sellers in the housing market are (i) aware of a LUST and (ii) 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 (i) and (ii) 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, and there may be a lingering social stigma (Messer et al, 2006; Gregory and Scatterfield, 2002).

In this paper, I ask five research questions. First, does being near a LUST affect property values, and how does this change when cleanup is undertaken and completed? Second, does the effect of leaks on home values depend on the presence of the primary exposure pathway (private groundwater wells)? Third, how do prices vary with additional information on well water contamination? Fourth, does LUST contamination and cleanup deter home transactions, and if so, is there evidence of "self-selection" into the sample of home sales? Fifth, what are the implications towards estimating the national benefits of the UST program via hedonics, versus an alternative stated preference approach?

To answer these questions, I conduct a hedonic house price study based on a unique and comprehensive dataset of homes and transactions, neighborhood characteristics, 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. Repeat sales and spatial econometric models are estimated to check the robustness of the results.

A unique contribution of this paper is that instead of measuring the risk solely by proximity to the disamenity, as done in many previous studies (Boyle and Kiel, 2001; Farber, 1998), I also account for home-specific variation in information and pollution, which I measure with domestic groundwater well tests from the Maryland Department of Environment (MDE). In general, I find that the typical LUST has little effect on the price of nearby homes (e.g., within 500 meters), even if a home relies on a private well. However, I do find a 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.

To examine the fourth question of whether LUSTs deter transactions, I estimate a model of annual sale occurrence at individual homes. I argue that this approach is superior to looking at transaction rates in an area because it uses a more spatially refined unit of observation, and individual house characteristics (in addition to characteristics of the neighborhood) can be used to explain sales activity. This allows me to examine whether higher-end homes are more likely to sell in the face of pollution, which could imply that hedonic methods underestimate the benefits of cleanup.

I find that transactions are half as likely to occur when a nearby LUST is undergoing "active cleanup" (e.g., tank removal, soil excavation, pumping and treatment of groundwater), an effect that is more prominent among homes relying on private wells. Visual cues associated with cleanup may lead to revisions in risk perceptions, and given the unpublicized nature of most LUSTs, this may be the first event making people aware of the pollution problem.

These findings raise questions about whether hedonic property value methods *are* the best approach to estimate the national benefits of the UST program. Prices depend on buyers' and sellers' risk perceptions, which in turn depend on public knowledge, both of which in the case of LUSTs remain unclear, and are difficult to measure on a local, let alone a national, scale. Moreover, compiling the necessary data on USTs and leaks for a broader hedonic study would be extremely difficult, if not impossible.

The rest of this paper is organized as follows. Section II provides some background information on LUSTs. Section III reviews the literature. The theoretical and empirical models are outlined in section IV. I describe the data in section V, and present the results of the hedonic model in section VI. Section VII presents the annual sale occurrence model. Section VIII concludes and discusses the policy implications.

II. Background

II.A. Regulatory Background

In the early 1980s, the states and the US Environmental Protection Agency (EPA) first became aware that a large number of the USTs at gas stations, factories, refineries, and other commercial and industrial facilities were leaking contaminants into the surrounding soil, and surface- and groundwater. In 1984 Congress addressed this issue by adding Subtitle I to the Resource Conservation and Recovery Act, which created a comprehensive program regulating USTs.

As a result, in 1986 the EPA required owners to register *all* existing and new USTs to the appropriate State agency. In 1988, technical standards were issued, requiring that (i) existing tanks be retrofitted with corrosion protection by December 22, 1998, (ii) new tanks be constructed to follow specified corrosion protection standards, and (iii) all tanks install overfill and spill protection and release detection devices. Owners of leaking tanks were to be held liable for cleanup, and to provide financial assurance for the cost of corrective action and for compensating third parties for any damages. The EPA encouraged the States to develop their own UST programs, for which they could seek formal approval.

As of September 2010, there are about 495,000 known UST releases throughout the United States. Cleanups have been initiated at 470,460 LUST sites, and completed at 401,874 sites (US EPA, 2011). For comparison, there are currently a total of 1,281 sites on the Federal National Priorities List (NPL) and 346 sites have been deleted.[5] With the cost of cleanup ranging from a few thousand to millions of dollars at each LUST (US EPA, 2004; Khan et al., 2004), and given the extensive Federal and State involvement, it is useful and important to find out what the benefits of cleanup and prevention are.

II.B. Exposure to and Effects of LUST Pollution

Contaminants from a LUST 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. Adverse human health effects may arise from 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.[6]

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[5] The 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, http://www.epa.gov/superfund/index.htm, accessed October 20, 2010).

[6] US EPA, http://water.epa.gov/drink/info/well/, accessed October 20, 2010.

The majority of the EPA 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.[7] Motor fuel can contain harmful additives, such as Methyl tertiary butyl ether (MTBE), a former gasoline additive and suspected carcinogen.[8]

II.C. Public Knowledge of LUSTs

Many hedonic studies rely on proximity to a disamenity to measure risks (Boyle and Kiel, 2001; Farber, 1998), and in doing so assume that buyers and sellers in the market are aware of the disamenity and associated events. 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. These facilities often provide services, which the public may find useful and not necessarily associate with a potential environmental disamenity. 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.[9]

The Maryland Department of Environment (MDE) requires a responsible party (usually the UST owner) to notify the public only in the most severe cases,

[7] US EPA, http://www.epa.gov/safewater/contaminants/index.html#listmcl, accessed July 28, 2009.
[8] Toccalino (2005); and US EPA, http://www.epa.gov/MTBE/, accessed January 20, 2009.
[9] 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."

where a corrective action plan is necessary.[10] 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. Testing is, however, a prerequisite for the sale of *any* home using a private groundwater well.[11]

It is unclear if residents are aware of a LUST just because they live in close proximity to it. However, if 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. In summary, residents at homes where testing occurs can be presumed to be well-informed about the LUST and contamination at their homes.

III. Previous Literature

III.A. The Hedonic Price Method

In the absence of marketplaces where environmental quality or health risks are traded, economists resort to revealed- and stated-preference methods for placing a monetary value on these goods. Hedonics is a commonly used revealed preference approach. In a differentiated good market (e.g. housing) the matching of buyers and

[10] 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).
[11] Suzanne Marsh, Maryland Real Estate Agent, personal communication, 27 Mar. 2009.

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. This is commonly referred to as Rosen's first stage.

To estimate non-marginal welfare changes one may have to pursue the second stage of Rosen's procedure, and estimate the underlying demand functions.[12] 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 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.,

[12] 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 housing characteristics. 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, and relying on differences in the curvature of the hedonic price, and bid and offer functions.

2007) and health risks.[13] There are several areas of research that are particularly important to understanding the effects of LUSTs on home values.

III.B. Water 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. 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 home price in Wichita, Kansas, which is not surprising since most (if not all) of the homes were connected to the public water system, implying there were no immediate health risks.

Focusing on two towns in Maine where residents do rely on private wells, 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.

The majority of hedonic studies on water quality focus on surface water (Boyle and Kiel, 2001). For example, Leggett and Bockstael (2000) analyze the effect of fecal coliforms in the Chesapeake Bay on home values in Anne Arundel

[13] See Boyle and Kiel (2001) for a review of hedonic studies organized by environmental disamenity. Farber (1998) and Jackson (2001) review the hedonic literature on undesirable land uses, especially Superfund sites.

County, Maryland, and find that values do decrease. They also emphasize the need to control for other disamenity effects (e.g. noise, odor, and aesthetics) associated with the source of contamination; not doing so introduces omitted variable bias.

III.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 hedonic 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 NPL, cleanup being undertaken, and cleanup completion). Each event represents new information that revises public perceptions of environmental and health risks, and in turn, affects property values. The change in the premium for distance from a site reflects a change in residents' welfare.

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, there is significant variation across studies, ranging from $190 to $11,450 per mile (Boyle and Kiel, 2001). 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.

Some researchers explicitly model risk perceptions and how individuals update their beliefs due to new information. Focusing on a Superfund site in Grand Rapids, MI, Gayer et al. (2000, 2002) are able to estimate the value per statistical cancer case avoided, which they find to be \$3.9-8.3 million. Similarly, Davis (2004) finds the value to avoid a statistical case of pediatric leukemia to be \$3-9.2 million.[14]

Most of the above studies only focus on a small subset of contaminated sites that may not be representative of all sites in the US. Greenstone and Gallagher (2008) conduct a nationwide study to see whether median home prices within a census tract are affected by Superfund sites.[15] They implement a quasi-experimental framework that reduces omitted variable bias (from the non-random distribution of sites) by exploiting the initial Superfund selection rule. They find that the listing of a Superfund site on the NPL does not affect median home prices, and conclude that, on average, the remediation costs outweigh the benefits.

Gamper-Rabindran and Timmins (2010) recently revisit this analysis and find that after accounting for a finer spatial resolution and within tract heterogeneity, the deletion of a Superfund site from the NPL does significantly increase house prices. They also find considerable heterogeneity in the effects of Superfund sites on home values, which confirms Kiel and Williams's (2007) earlier findings.

[14] Davis (2004) does not specifically analyze a contaminated site, but rather how being in a County with an abnormally high and unexplained rate of childhood leukemia affects property values.
[15] Technically speaking this is not a hedonic analysis, Greenstone and Gallagher (2008) estimate the median home price within a census tract as a function of aggregated statistics of the housing stock and the status of Superfund sites within that tract.

III.D. LUSTs and Residential Property Values

While there is a significant 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 presumably more local.[16] LUSTs are comparatively homogeneous in that contamination mainly consists of petroleum products, and the sites are generally gas stations, or other similar types of commercial and industrial facilities.[17] 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 revealed preference studies on LUSTs and residential property values.[18] Simons et al. (1997) estimate a hedonic model using a cross-section of home sales in 1992 in Cuyahoga County, Ohio, and find a 17% depreciation among homes within 300 ft of a registered LUST. They find no effect associated with proximity to registered non-leaking tanks or non-registered LUSTs. Simons et al. (1999) analyze

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[16] For example, Rice et al. (1995) find petroleum groundwater plumes in California rarely extend beyond 250 feet from a LUST. In this paper I find plumes migrated offsite at only 27 (19.6%) of the LUSTs. In contrast, hedonic studies on Superfund sites find property values are sometimes affected miles from the site.

[17] The UST program explicitly targets petroleum contamination, but USTs that store other hazardous substances are regulated under this program as well (EPA, 2011). Such hazardous substances are also regulated by other federal programs, such as RCRA. In this study I focus on UST facilities that store petroleum products and that are regulated by the Maryland Department of Environment's Oil Control Program.

[18] Simons and Winson-Geideman (2005) conduct a stated preference study across eight States (Kentucky, Pennsylvania, Ohio, Alabama, Illinois, South Carolina, West Virginia, and Texas). They ask respondents to bid on hypothetical homes and find that (i) LUST activity reduces the likelihood that a respondent will bid, (ii) bids are on average 31% lower when the groundwater is contaminated, and (iii) this decline in home bids was consistent across states, ranging from 25-33%.

home sales from 1994-1996 in Cuyahoga County, and find that LUST "contamination" from nearby gas stations reduces home values by 14-16%.[19] 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 the cross-sectional nature of these studies, one must use caution when interpreting these 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), where we emphasized the need to exploit both spatial *and* temporal variation in identifying the causal effects of LUSTs on home values.[20]

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, in Zabel and Guignet we observe home sales before and after the leak, allowing us to establish a pre-leak baseline, and analyze how prices change upon the discovery of a LUST, and completion of a leak investigation. In other words, we implemented a difference-in-difference type of methodology. We examined home prices within 100, 200, 500, 1000, and 2000 meters of a LUST, and checked whether the impact of a leak varied

[19] 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 typical hedonic study. Instead they compare the actual sales price to the predicted price from a hedonic regression that did not explicitly account for LUSTs.

[20] Zabel and Guignet (2011) is a revised version of a publicly available NCEE working paper, Zabel and Guignet (2010).

depending on the severity of contamination, the presence of an exposure pathway, and publicity surrounding the site. In general, we found that the typical LUST had little effect on home values, but more publicized (and more contaminated) sites can cause up to a 10% depreciation at homes in close proximity (i.e., up to 1,000 meters).

In this dissertation chapter, I further exploit this quasi-experimental framework by 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 facilities, which 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 (see section IV.C).

I also extend on Zabel and Guignet's (2011) study by estimating a repeat sales model, analyzing how prices are affected during cleanup activities, and investigating how leaks impact transaction rates at individual homes. In contrast to previous work, in this study I utilize home-specific variation in information and environmental quality, namely well tests and correspondence from MDE.

III.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 price premium for distance of a home from the disamenity, even though households may in fact hold such a premium if they were aware of the disamenity. Second, 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.

I examine the home price impact of proximity to a LUST and various events (e.g. leak discovery, cleanup undertaken, and cleanup completion), which represent new risk information. 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.

IV. The Model

IV.A. Theoretical Framework: What is the Effect of LUSTs on Home Prices?

I argue that the implicit price of proximity to a pollution source, such as a UST, reflects perceived environmental and health risks, as well as other amenities and nuisances. However, taking advantage of informational events such as leak discovery, cleanup, and well testing, allows me to identify the implicit price of pollution without these confounding effects.

In what follows I present a simple model to guide my empirical work. I assume a state dependent expected utility framework, where there are two states: (i) "Good" where a household experiences no adverse health or environmental outcomes from a leak and receives utility $U(x, UST, m)$, and (ii) "Bad" where the household does experience adverse outcomes, and receives utility $V(x, UST, m)$.[21] Let m denote a numeraire composite good, x is home and neighborhood characteristics (unrelated to USTs), and UST is proximity to (or density of) nearby UST facilities, regardless of whether a leak has occurred.

A household derives utility directly from the housing services provided by x, as well as UST facilities (such as gas stations) that offer goods and services, and possibly nuisances (e.g. displeasing aesthetics, traffic congestion, crime, and noise). When a household chooses a home they also choose a location, which comprises all attributes of that location, including UST. I assume that (*i*) utility is weakly higher in the "good" state $\left(U(\cdot) \geq V(\cdot)\right)$, and (*ii*) the marginal utility of income (MUI) is strictly positive in both states $\left(\frac{\partial U}{\partial m} > 0,\ \frac{\partial V}{\partial m} > 0\right)$.

A household's expectations are based on subjective, or perceived, probabilities. The perceived probability of realizing the "bad" state is $\pi = \pi(UST, I)$, where I denotes information about LUSTs and groundwater contamination (e.g. leak occurrence, cleanup, and well contamination). Notice that simply living near a non-

[21] This is an application of a theoretical model first developed by Hallstrom and Smith (2005), who model the effect of perceived hurricane risk on property values.

leaking UST may affect risk perceptions. For example, a household may worry about a potential leak occurring in the future.

The household maximizes its subjective expected utility by choosing a housing bundle $[x, UST, \pi(UST, I)]$ and the numeraire m. Perceived risk is implicitly chosen when choosing a home and its location. Formally,

$$\max_{x,UST,I,m}\big(1-\pi(UST,I)\big)U(x,UST,m)+\pi(UST,I)V(x,UST,m) \qquad (1)$$

$$s.t. \quad y \geq P\big(x, UST, \pi(UST, I)\big) + m$$

where y is exogenously determined income, and $P(\cdot)$ is the hedonic price function. Under assumption *(ii)* the budget constraint holds with equality. Solving for m in the budget constraint and plugging it into the expected utility function yields,

$$\max_{x,UST,I}\big(1-\pi(UST,I)\big)U\Big(x,UST,y-P\big(x,UST,\pi(UST,I)\big)\Big) \qquad (2)$$

$$+\pi(UST,I)V\Big(x,UST,y-P\big(x,UST,\pi(UST,I)\big)\Big).$$

The first order condition (FOC) with respect to UST is,

$$\frac{\partial P}{\partial UST}+\frac{\partial P}{\partial \pi}\frac{\partial \pi}{\partial UST}=\left[-\frac{\partial \pi}{\partial UST}\ \frac{[U-V]}{E(MUI)}\right]+\left[\frac{(1-\pi)\frac{\partial U}{\partial UST}+\pi\frac{\partial V}{\partial UST}}{E(MUI)}\right] \qquad (3)$$

where *E(MUI)* denotes the expected marginal utility of income. Analogous to Rosen's (1974) standard result, in equilibrium the optimizing household equates the marginal implicit price of UST, as shown in the left-hand-side (LHS) of (3), with their marginal willingness-to-pay (MWTP) for UST, which is the sum of the two bracketed terms in the right-hand-side of (3). The first bracket is the MWTP for a marginal change in the perceived probability of realizing the "bad" state, and the second is the net MWTP for services and nuisances offered by the UST facility.

In this model additional information regarding leaks and groundwater contamination is assumed to only affect expected utility through perceived risks. Taking the FOC of (2) with respect to *I* demonstrates that this marginal implicit price is a welfare measure based solely on a marginal change in perceived risks. Formally:

$$\frac{\partial P}{\partial I} = \frac{\partial P}{\partial \pi}\frac{\partial \pi}{\partial I} = -\frac{\partial \pi}{\partial I}\frac{[U-V]}{E(MUI)}\,. \tag{4}$$

The term on the LHS of (4) is the implicit price of risk information, which equals the expected incremental option price between the “good” and “bad” state $\left(-\frac{[U-V]}{E(MUI)}\right) \leq 0$, multiplied by the marginal change in subjective risk.

The sign of the effect of leak information on prices depends on how this information affects perceptions of environmental and health risks, i.e., the sign of $\frac{\partial \pi}{\partial I}$. For example, if the discovery of leak increases risk perceptions then prices would decrease. If a household is unaware of a leak or does not perceive this as a threat, then $\frac{\partial \pi}{\partial I} = 0$ and property prices would remain unchanged.

The main point is that proximity to a pollution source does not cleanly identify the implicit price of pollution because it is confounded by other amenities and nuisances posed by the site and surrounding area. In contrast, taking advantage of informational events such as leak discovery, cleanup, and well testing, identifies changes in home prices based solely on the pollution events.

IV.B. The Ideal Econometric Experiment

If the research objective is to study the benefits of the EPA’s Federal UST program, then ideally, from an econometric standpoint, one would like to take a nationally representative sample of homes and regard leak and cleanup events as if they were randomly assigned to these homes (see Angrist and Pischke, 2009). Unfortunately, this is not possible for two reasons. First, assembling a representative national dataset of property transactions, USTs, and LUSTs is unfeasible. Second, there is no reason to believe that leaks are random, and therefore if not properly controlled for, the estimated effect of a leak on home values may be biased.

Greenstone and Gallagher (2008) circumvent these issues when estimating the national benefits of the Federal Superfund Program. They conduct a "hedonic" analysis using median home prices at the census tract level for the entire US. They implement a quasi-experimental framework that exploits the initial selection rule for Superfund sites, which reduces omitted variable bias caused by the non-random distribution of sites. Specifically, they compare candidate NPL sites with hazard ranking scores just below and above the threshold for placement on the NPL.

This approach would not work in the context of LUSTs because (i) there is no centralized Federal database of LUST sites, (ii) the unit of observation (the census tract) is too spatially coarse to pick up any effects from LUSTs, and (iii) the census is taken every 10 years, an interval that is too long for most leak investigations and cleanups, which only last a year or two.

Alternatively, one might obtain home transaction data for several housing markets, but gathering the necessary UST data would be difficult. Records are maintained by the States, and there is no centralized database with detailed LUST event documentation. The State of Maryland does maintain an electronic database, but much of the key information remains in hard copy files. I spent over 200 hours reviewing and retrieving records from individual case files at MDE. Site-specific details are important because despite the fact that LUSTs involve a relatively homogeneous class of pollutants (petroleum by-products), I find substantial heterogeneity in pollution severity and investigation activities. For example, contamination plumes migrated to neighboring properties at about 20% of the LUST sites, active cleanup had been undertaken at half the sites, and leak investigations ranged from one day to over 10 years.

IV.C. Empirical Framework and Study Design

Given that nationwide or multiple-state approaches are not feasible, in this paper I focus on USTs and homes in selected housing markets in Maryland (see section V). I take several steps to minimize any omitted variable bias due to the non-random spatial distribution of LUSTs, as described below.

Consider a single housing market. 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 of its location, including UST facilities $(\boldsymbol{UST}_{ijt})$ and perceived environmental and health risks (π_{ijt}). Formally, $p_{ijt} = f(\boldsymbol{x}_{ijt}, \boldsymbol{UST}_{ijt}, \pi_{ijt})$, where $\boldsymbol{x}_{ijt}$ denotes home structure and neighborhood characteristics.

Risk perceptions are formed from a given information set about the disamenity and location: $\pi_{ijt} = \pi(\boldsymbol{UST}_{ijt},\ \boldsymbol{I}_{ijt})$. I posit that information has two components, $\boldsymbol{I}_{ijt} = [\boldsymbol{LUST}_{ijt}, \boldsymbol{Test}_{it}]$. The vector $\boldsymbol{LUST}_{ijt}$ denotes the presence of a LUST 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.

Interaction terms between distance to a pollution source and contamination/cleanup events is a common identification strategy in hedonic studies (Boyle and Kiel, 2001; Farber, 1998). A unique aspect of my study is the inclusion of home-specific information regarding leaks and pollution in private groundwater wells, denoted $\boldsymbol{Test}_{it}$. MDE staff will test a domestic well if they suspect that it is contaminated by petroleum from a LUST. Residents of these homes receive letters explaining the situation, requesting to test their well, and the test results. 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

$$\ln p_{ijt} = \boldsymbol{x}_{ijt}\boldsymbol{\beta} + \boldsymbol{UST}_{ijt}\boldsymbol{\gamma} + \boldsymbol{LUST}_{ijt}\boldsymbol{\theta} + \boldsymbol{Test}_{it}\boldsymbol{\alpha} + v_j + \boldsymbol{M}_t + \varepsilon_{ijt} \qquad (5)$$

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 (that I later assume to be normally distributed).[22] 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, then 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 home values. The coefficient $\boldsymbol{\alpha}$ is the effect of groundwater well testing and contamination on the value of a home.

In addition to (5), I estimate several variants of it. The first entails a two-stage control function or propensity score type of approach (Wooldridge, 2002, Chp. 18). This framework effectively compares the price of homes around leaking UST

[22] In the specifications I allow the disturbances to be correlated at different levels of spatial aggregation, including clustering at the census block group or tract level, or more formal spatial autocorrelation models (see LeSage and Pace, 2009).

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 UST facility that are correlated with the discovery of a LUST. 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 price effects in order to identify $\boldsymbol{\theta}$.

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

$$PS_k = Prob(leak_k) = \Phi(\boldsymbol{tank}_k \boldsymbol{\psi}) \tag{6}$$

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 USTs, 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. I estimate $\boldsymbol{\psi}$ in the probit model shown in (6) via the method of maximum likelihood. I then form the predicted propensity of a leak at each UST facility $\left(\widehat{PS}_k = \Phi\left(\boldsymbol{tank}_k \hat{\boldsymbol{\psi}}\right)\right)$.

The expected number of leaks around a home is then calculated by summing $\widehat{PS}_k$ for all tank facilities within the vicinity of each home,

$$\widehat{leak}_i = \sum_{k \in \Im_i} \widehat{PS}_k \tag{7}$$

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 $\widehat{leak}_i$, to (5), yielding:

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

$$+\boldsymbol{Test}_{it}\boldsymbol{\alpha} + v_j + \boldsymbol{M}_t + \varepsilon_{ijt} \quad . \qquad (8)$$

Similar to a propensity score model, in (8) 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).

The second variant of (5) I estimate is a repeat sales model, where unobserved time invariant characteristics associated with a home and its specific location are differenced out. Suppose home *i* was sold in some earlier period $s < t$, then the repeat sales model is

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

$$+\Delta\boldsymbol{Test}_{\boldsymbol{its}}\boldsymbol{\alpha} + \Delta\boldsymbol{M}_{ts} + \Delta\varepsilon_{ijts} \qquad (9)$$

where Δ denotes the change in the 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 (5) is a spatial autoregressive model (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 time-varying confounders. This lag is basically a weighted average of home prices within some predefined neighborhood. The model is presented below in matrix notation,

$$\boldsymbol{P} = \rho\boldsymbol{WP} + \boldsymbol{X\beta} + \boldsymbol{UST\gamma} + \boldsymbol{LUST\theta} + \boldsymbol{TEST\alpha} + \boldsymbol{M} + \boldsymbol{\varepsilon} \qquad (10)$$

where $\boldsymbol{P}$ is a $n \times 1$ matrix containing the natural log of the price for all sales, $\boldsymbol{W}$ 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 all unobserved and potentially confounding characteristics associated with the location of a home.

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).[23] 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.[24] This dataset contains four main components: (i) registered UST facilities, (ii) leak investigation and remediation cases, (iii) single family home sales, and (iv) well contamination test results.

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

[23] Baltimore County does not include the City of Baltimore, which is considered a separate county (FIPS 24510).

[24] According to the 1990 census, virtually all homes in Baltimore City are served by the public water system. 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.

Frederick (459) Counties.[25] 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 (table 2). 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. During 1996-2007 leaks were discovered at 138 (3.92%) of these registered UST facilities.

V.B. Leaking Underground Storage Tanks

MDE's Oil Control Program provided data on 42,100 oil "cases" in Maryland, which includes routine compliance, 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 were first opened during 1996-2007.

Case documentation is available only at the MDE office in Baltimore, where I spent over 200 hours reviewing individual case files. 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 facility with 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

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

facility (see table 3).[26] These facilities are continually regulated by the UST program, and face ongoing monitoring, and procedural and system compliance requirements. Therefore, this subset of LUST sites is particularly relevant for studying the benefits of the program.

Of these 138 cases, 34 (24.6%) LUSTs are in a private well area, and at 27 of them (19.6%) there was evidence confirming that contamination migrated to neighboring properties. 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 closed 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.[27] The hedonic analysis

[26] Leaks at non-registered facilities are the result of past land uses. These sites could currently be used for a variety of activities, and so there is no clear counterfactual. In contrast, the obvious counterfactual to leaks at registered tanks is non-leaking registered tanks. In an earlier hedonic study we examine leaks at both registered and non-registered USTs (Zabel and Guignet, 2010).

[27] 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.

focuses on the 132,840 sales from 1996-2007 for this set of homes.[28] 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 $125,931 in Baltimore City (2007$).[29]

Descriptive statistics of the home characteristics are shown in table 4. 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.[30] I define neighborhoods according to the 2000 Census block groups for Baltimore and Frederick counties, and by census tracts for Baltimore City.[31] 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 open space areas).

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

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[28] I restrict attention to arms' length sales, and exclude home sales with a sale 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.

[29] All 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).

[30] 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.

[31] 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.

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 5 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 in the more rural private well areas, which is where households are potentially exposed to contaminated groundwater.

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 (3 in Baltimore and 8 in Frederick counties). Often MDE found no, or minimal, contamination, and it was therefore not necessary to continue testing. Figure 4 shows how many well tests took place prior to the sale of each home, 16 homes had only one well test prior to the sale, but 33 homes were tested multiple times.[32]

[32] 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.

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 was found in 11 domestic wells and MTBE in 19 (see table 6).[33] Granulated active carbon (GAC) filters, which essentially eliminate all pollutants, were installed and maintained by MDE at nine of the 10 home sales where pollution levels exceeded the regulatory standards.

Under Maryland Real Estate Disclosure laws, the sale of *any* home on a private well is conditional on a satisfactory well test.[34] These are separate tests that are not associated with Maryland's Oil Control Program. Nevertheless, since LUST contamination was previously found or suspected by MDE, these routine tests may find contamination, or bring the LUST to the attention of the prospective buyer, especially if the leak and well tests by MDE were relatively recent events. On average, the most recent MDE-conducted test relative to the sale date was 1.55 years prior to the sale date (the median is 124 days). At 32 (64%) of the MDE-tested homes, testing occurred both before and after the transaction, implying sellers and buyers were likely aware of the LUST and groundwater contamination.

[33] 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.

[34] Unfortunately I do not observe these well tests; I only have access to the tests undertaken by MDE as part of their investigations.

VI. Hedonic Regression Results

VI.A. Base Hedonic Model Results

In the first set of hedonic price regressions I estimate several variants of equation (5). The dependent variable is the natural log of the sale price (2007$). In table 7, I estimate a single hedonic price function for all three counties.[35] 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 effects of a UST and leak and cleanup events on home values 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.[36] 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 7.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

[35] 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. 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.

[36] Other distances including 100, 200, 500, and 1,000 meters were estimated, but not reported here. The results are robust to the chosen distance interval. See Zabel and Guignet (2010).

with models where I better control for confounding influences and heterogeneity. Only the coefficient estimates of particular interest are shown, but the sign and significance of those not shown are as expected.[37] The -0.0201 coefficient on *non-leaking UST within 0-500m* suggests that homes near a UST sell for about 2% less, and homes near a UST that will eventually leak tend to sell for 7% less (as seen by *LUST within 500m*).

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. It is possible that this counterintuitive appreciation is 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 7.A suggests a small and statistically insignificant price effect when cleanup is undertaken, and the investigation subsequently completed.

Model 7.B includes neighborhood fixed effects. Accounting for unobserved heterogeneity in this fashion does reduce the counterintuitive effect of leak discovery by more than 50% relative to model 7.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 (see figures 2 and 3), so the coefficient on *leak discovered* is unlikely to pick up unobserved effects

[37] The full results are available upon request. The full results for the hedonic models estimated separately for each county (tables 8, 9, and 10) are displayed in the appendix of this chapter.

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 open because contamination was found during redevelopment. This is one potential explanation as to why leak discovery is associated with an increase in home values.[38] It is also possible that when there is pollution, only the most attractive homes are sold, implying an upward bias if there is unobserved “self-selection” into the sample, an effect I examine in section VII.

To better control for unobserved heterogeneity that may vary over time or within a neighborhood, in model 7.C I add the natural log of the median price of prior sales within 500 meters of a home.[39] 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 influences on home prices. This adds explanatory power, but does not change the LUST related coefficients.

Model 7.D is a repeat sales model. Following equation (9), the home and location specific time invariant characteristics are differenced out, and the median neighbor price is included to help control for unobserved local trends. The coefficient on *leak discovered* is much smaller, suggesting only a 1.6% appreciation, which is not

[38] 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 this 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.

[39] This is the median price of all single-family home sales 3 years prior and within 500 meters.

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 possible residual perception of risk or public stigma even 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.

In tables 8-10, I repeat the above regressions for each county individually. There are too few sales to estimate a repeat sales model for each county. Instead, spatial autoregressive and autocorrelation models are estimated following equation (10).[40] Again, only the coefficients of interest are displayed, but the full results are provided in the appendix to this chapter. Focusing first on Baltimore City (table 8), in the specifications controlling for unobserved neighborhood effects (models 8.B-8.C) we see no significant effect of LUSTs on home prices. This holds even in model 8.D, which includes a spatial lag and allows for spatial autocorrelation.

The Baltimore County results (table 9) 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 negative effect on prices. Models 9.B through 9.D again suggest a counterintuitive 5% appreciation in home prices upon the discovery of a leak. There is some evidence that home values appreciate 2.68-5.41% upon closure of a leak investigation, in models 9.C and 9.D, respectively.

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

In Frederick County (table 10), the results suggest that the discovery of a LUST leads to a 2.53-4.68% increase in home prices (although this is only marginally significant in some specifications). We see some 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 if so, if this affects the impacts of a LUST. For example, are home values affected differently by the mere presence of a gas station versus an industrial facility? As shown in table 2, 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 of the site was not specified on MDE's UST inspection report.

In table 11, for Baltimore City (model 11.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, being within 500 meters of a gas station is associated with 6% lower home prices, all else the same, although this effect is not statistically significant at the conventional levels (p-value = 0.11). When the use of the UST facility is not specified, the prices of homes within 500 meters 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). In contrast, for Baltimore (model 11.B) and Frederick (model 11.C) counties, 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.

In general, the estimated impacts of the discovery of a leak, cleanup, and closure of a leak investigation (as displayed in table 11) are not affected by allowing the baseline UST effects to vary. One exception, however, is that model 11.A suggests that in Baltimore City, home prices decrease by 9.97% upon closure of a leak investigation.

In table 12, I focus on Baltimore and Frederick Counties, and examine whether the presence of an exposure pathway matters by estimating separate regressions for homes in private well areas versus those in areas served by the public water system. Again we see that leaks, on average, have a small and often insignificant effect on home prices. Leak discovery is still associated with a 2.95% appreciation in value for homes that rely on private wells, but this is not significantly different from zero. In contrast, in areas connected to the public water system, and hence the primary exposure pathway to contamination is not present, the discovery of a LUST is associated with a 4.21% increase in home prices.

VI.B. Hedonic Results from a Refined Quasi Experiment

The estimation results in table 13 focus only on homes within 500 meters of a registered UST, and as such, this hedonic model is a refined quasi experiment that only compares homes near USTs where a leak did and did not occur. Model 13.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 of sales (which is not statistically significant).

Even in this refined model, the only significant result is the unexpected 4.64% appreciation upon the discovery of a leak. A similar result holds even when focusing on homes with private wells (model 13.C).

An alternative two-step "propensity score" type of model, as shown in equations (6)-(8), is estimated for models 13.B and 13.D. Since the treatment (i.e., the discovery of a leak) is technically "assigned" to USTs, and not homes per se, I estimate the discovery of a leak at a UST facility (eq. 6). 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).

The estimated average marginal effects from the probit models are displayed in Table 14. Model 14.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 an exposure pathway is present and USTs are more extensively regulated and monitored. In Model 14.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 depth to the groundwater aquifer is relatively large. In models

14.C and 14.B I include census block group characteristics, which have statistically insignificant effects on the probability of a leak.

I use the estimated coefficients from the first step to estimate the probability (or propensity) of leak discovery at each UST facility. Focusing on model 14.B, 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.[41] Figure 6 displays the distribution of predicted propensities, and shows that the common support is fairly wide.

I next calculate the "propensity score" or predicted number of leaks for each home by summing up the predicted leak probability for all USTs within 500 meters (see eq. 7), and estimate the hedonic model (eq. 8). In table 13, model 13.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. 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 effects of a LUST on home prices, except for the 4.03% appreciation upon the discovery of a LUST. The results are similar when focusing just on homes that rely on private wells (model 13.D). [42]

[41] The predicted propensities, and subsequent hedonic results, do not change significantly when the other models in table 15 are used.

[42] 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.

VI.C. Hedonic Results with Well Tests

The regressions in table 15 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 15.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 15.B and 15.C focuses only on the sale of homes that are most at risk (i.e., 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, but despite this low number there is a fairly large and statistically significant depreciation. To make sure these dummies are not just picking up unobserved heterogeneity, in table 16 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 homes where the well is tested. There is little change in the *Well Tested* coefficient. In fact, this strengthens the result. I calculate the impact as:

$$Well\ Test\ Impact = \{\exp(\alpha_{\text{Well Tested}} - \alpha_{\text{Sold before Well Test}}) - 1\} \qquad (11)$$

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

Regressions not reported in this dissertation show that there is a significant depreciation even when a test reveals no contamination. 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 contamination below the standard.

VII. Do LUSTs Deter Home Sales?

VII.A. Sale Probability Model

There are three reasons why it is important to understand whether LUSTs deter sales. First, hedonics may not capture welfare losses associated with a seller's inability, or reduced ability, to sell their home. Second, hedonic methods assume that the occurrence of a sale does not depend on unobserved characteristics that also affect price (or that are at least not correlated with the variables of interest). However, if in the presence of pollution only the most desirable homes are sold, and the characteristics making such homes attractive are not observed, then such "self-selection" into the sample of sales implies that hedonics underestimates the effect of pollution on home values. Third, statistical identification in the hedonic regressions is more difficult if the disamenity of interest further deters sales. LUSTs are a very localized pollution event and the primary exposure pathway (private wells) exists mainly in less dense rural areas, thus there are already relatively few sales available for identifying the implicit price of LUSTs.

Suppose a home is sold in year t if the maximum bid is greater than or equal to the current owner's reservation value of not selling and continuing to live in the home. In equilibrium the hedonic price surface is the upper envelope of buyers' bid functions, therefore we observe a transaction of home i in period t ($sold_{it} = 1$) if the market value of the home is greater than or equal to the seller's reservation value. I do not observe the seller's reservation value, and so I must estimate a reduced form model,

$$E(sold_{it}) = \tilde{G}(\boldsymbol{x}_{it}, \boldsymbol{UST}_{it}, \boldsymbol{LUST}_{it}, \boldsymbol{M}_t) \tag{12}$$

where $\tilde{G}\{\cdot\}$ is a given cumulative distribution function.[43] Recall that $\boldsymbol{x}_{it}$ denotes a vector of home structure and location characteristics, $\boldsymbol{M}_{it}$ is a vector of year dummies to account for overall housing market trends, and $\boldsymbol{UST}_{it}$ and $\boldsymbol{LUST}_{it}$ are vectors denoting proximity to UST facilities and LUST discovery and cleanup activities, respectively.

VII.B. Data for Sale Probability Model

I construct a panel of 212,068 single family homes each year from 2000-2007 (including homes that did not sell).[44] Observing these parcels over 8 years yields a total of n=1,696,544 observations. Table 17 displays the number of parcels in each county and whether they are connected to the public water system or use a private well. Among these parcels, the number of sales in each county by year is displayed in table 18. As seen in figure 5, there is a higher sale rate in Baltimore City than the other more suburban/rural counties of Baltimore and Frederick, and there is a similar time trend across the counties.

[43] I model annual sale occurrence using probit and fixed effect logit models, and thus, depending on the model, assume $\tilde{G}\{.\}$ is either a Normal or Type II Extreme Value cumulative distribution function.
[44] This is not all single family homes, I restrict attention to the subset where the same tax identification number remained from 2000-2007, and a new house was not built. This is a relatively constant stock of homes. It is not always clear why a parcel's tax identification number changes, but sometimes this occurs because a parcel is put into a new land use, a new structure is built, or it is split into several lots or merged with neighboring parcels.

VII.C. Sale Probability Results

I estimate several variants of equation (12). Only the coefficients of interest are displayed in tables 19-21, but all attributes in table 4 are included in the right-hand side of the model. In table 19, I estimate a separate probit model for each county and display the average marginal effects. Comparing models 19.A-19.C, only the signs on the coefficients associated with *cleanup* and *post-closure* are the same across all counties. I am particularly interested in the negative effect of cleanup on transactions, an effect that is particularly strong in Baltimore City. Among the Baltimore City homes analyzed, the probability a home is sold in a given year is 7.5%, but this is reduced by 3.57% when a LUST is undergoing active cleanup (e.g., excavation of soil). Therefore, the home is almost half as likely to sell! In contrast, Howland (2004) finds that transaction rates of industrial parcels in Baltimore City were not affected by contamination.

Visual cues associated with cleanup may make buyers and sellers aware of the LUST site for the first time, or cause them to perceive the risks as more severe (Dale et al., 1999; Messer et al, 2006). Residents may also find cleanup efforts bothersome and aesthetically displeasing (Weber et al., 2001). These visual cues may lead to public stigma (Gregory and Scatterfield, 2002), thus deterring buyers from looking at homes in the neighborhood, and/or discouraging sellers from entering the market until the situation is resolved.

In table 20, I estimate the probability of a sale separately for homes in private well and public water areas in Frederick and Baltimore Counties. Comparing the coefficients across models 20.A and 20.B suggests that cleanup especially decreases sales in private well areas. The average home in a private well area has a 3.2% probability of being sold in a given year, but this decreases by 1.45 during the cleanup of a LUST, a 45% decrease in the probability of a sale.

The finding that cleanup activities are a stronger deterrent of transactions among homes with private wells is confirmed using a fixed effect logit, which conditions out all time invariant home specific characteristics (Chamberlain, 1980), thus reducing omitted variable bias.[45] Homes in both private well and public water areas are used in estimating model 20.C, and interaction terms are included to allow the effects of LUSTs to differ.[46] Note that the marginal effects could not be calculated due to the unobserved home-specific intercepts, so the estimated coefficients are displayed. The positive and occasionally significant coefficients corresponding to closure of a leak investigation suggest that sales activity rebounds back to at least the pre-leak levels once the perceptual reminders associated with cleanup cease, and the LUST is deemed safe by MDE. Thus there appears to be no post-cleanup stigma in terms of quantity of sales.

Table 21 examines whether "high-" versus "lower-end" homes are more or less likely to sell during LUST events. I focus on the homes where health risks are highest, those in private well areas that are within 500m of a UST. I define "higher-" and "lower–end" homes based on observed characteristics, namely construction quality and the distribution of assessed values. Interaction terms are included in

[45] Estimation of the fixed effect logit model requires variation in the dependent variable, and therefore only accounts for homes that were sold at least once during the study period.

[46] A likelihood ratio test confirms that this is the correct specification, the null that the probability of a sale is affected the same way by LUSTs in private well and public water areas is rejected at the 10% level (chi-sq=6.56, p-value=0.0873). The null hypothesis that transactions are affected by cleanup the same way in private well and public water areas is rejected with a chi-sq=4.30 (p-value=0.0380).

models 21.A-21.D to allow the effects of LUSTs on sales to differ for lower- and higher-grade homes.[47]

The negative and statistically significant coefficients corresponding to the interaction term *cleanup* × *low*, relative to the coefficients on *cleanup* × *high*, suggest that lower-end homes are far less likely to sell during cleanup activities. For example, the average home in Model 21.A has a 2.76% probability of being sold in a year, but when a LUST is undergoing cleanup this is cut in half! In contrast, the average high-end home has a 3.77% probability of being sold, and this is reduced to 3.56% during cleanup (a statistically insignificant change). This difference in the point estimates is robust to fixed effect logit estimations and various definitions of low and high quality homes (models 21.B-21.C). However, in all the models in table 20 I fail to reject the null that these effects are statistically different.

More research is needed, but this provides some evidence reflecting Simons et al.'s (1999) sentiment that hedonics may underestimate the effects of LUSTs because more desirable homes are more likely to sell in the face of pollution. If similar unobserved characteristics are affecting whether a sale takes place, then such "self-selection," would bias the hedonic results. It might be possible to control for such selection bias with a Heckman (1979) two-step or a propensity score matching approach (Wooldridge, 2002), but in practice it is difficult to find an exogenous variable that influences the occurrence of a sale but does not influence price, as is recommended for identification purposes.[48]

[47] Likelihood ratio tests across all four models fail to reject the null that higher and lower-end homes are affected differently across all LUST events.

[48] Under standard hedonic assumptions characteristics of the selling household would be the ideal identifying variable, but I unfortunately do not have this information.

VIII. Conclusion and Future Research

The goal of this study was to investigate how property values respond to potential and actual petroleum contamination from leaking underground storage tanks (LUSTs), and ultimately determine the feasibility of using hedonic methods to estimate the broader benefits of the national Underground Storage Tank (UST) program. The hedonic property value model is an attractive valuation technique because it relies on actual market behavior. However, disentangling the implicit price of LUSTs is challenging because they are relatively unpublicized pollution events, and the spatial distribution of UST facilities, and therefore 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 conduct a detailed study on home prices and transactions. 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 spatial 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.

In general, I conclude 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. It remains unclear whether residents who are merely living near a LUST always perceive it as a threat, or are even aware of it.

A unique aspect of this paper is that I account for 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 since 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, from a nearby LUST. Furthermore, the test results may reveal that the private well is in fact contaminated. This information may lead to changes in a household's perceptions of current risks, as well as potential risks in the future.

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.

I find that home transactions are half as likely to occur when a nearby LUST is undergoing "active" cleanup. Visual cues associated with cleanup (e.g., tank removal, soil excavation, and pump-and-treat devices) may lead to changes in risk perceptions, and given the unpublicized nature of most LUSTs, this may be the first event making people aware of the pollution problem. Sales activity rebounds once cleanup is complete and the leak investigation is closed, suggesting that once perceptual reminders cease and the risks are eliminated, there is no residual stigma towards the neighborhood, at least in terms of transaction rates.

An important issue to consider in expanding this analysis to a nationwide or multi-state hedonic study, and ultimately to estimate the benefits of the national UST program, is that details specific to individual LUSTs are extremely important, and add to the already daunting data collection task. There is no Federal LUST database, as in the case of other Federal programs, such as Superfund. Each State maintains its own records, and the quality and comparability may vary substantially.

An alternative approach is a nationwide stated preference study, where the researcher can directly address health risks, control for what information and risks are presented, and better understand how people perceive these risks. A stated preference approach also allows for a more valid counterfactual (i.e., what pollution levels would be in the absence of the UST program). Such a counterfactual is difficult in a hedonic study because the UST program has been in place since the mid-1980s, and is very proactive in preventing and minimizing damages.

Figures and Tables

Figure 1. Three Maryland Counties in Study Area and Public Water Service Area.

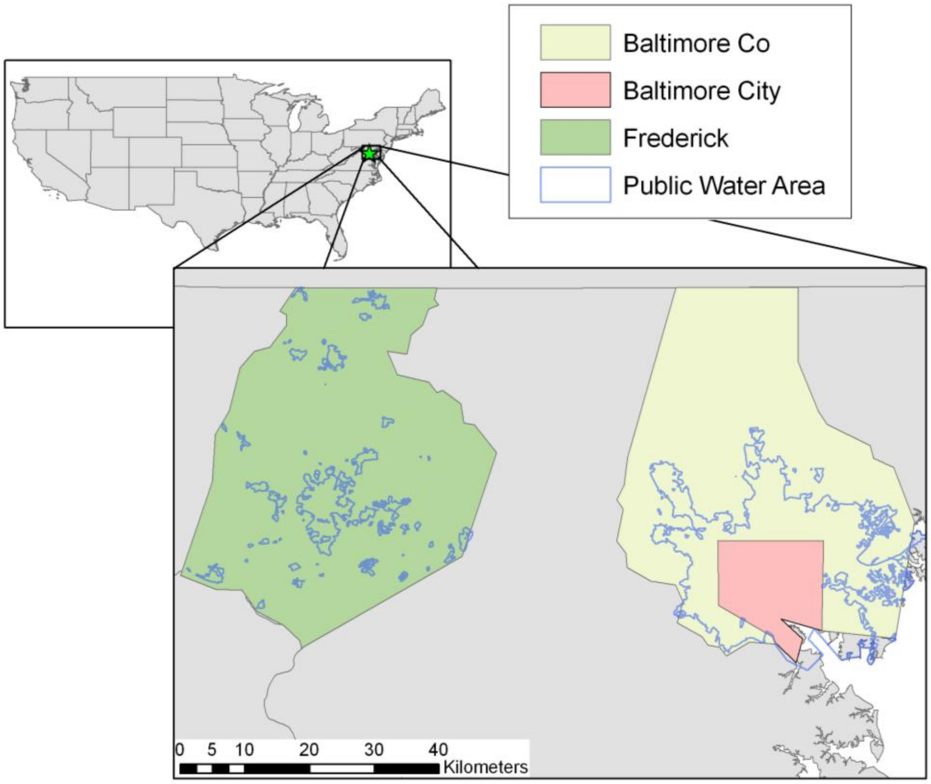


Figure 2. Registered Underground Storage Tanks and Leaks.

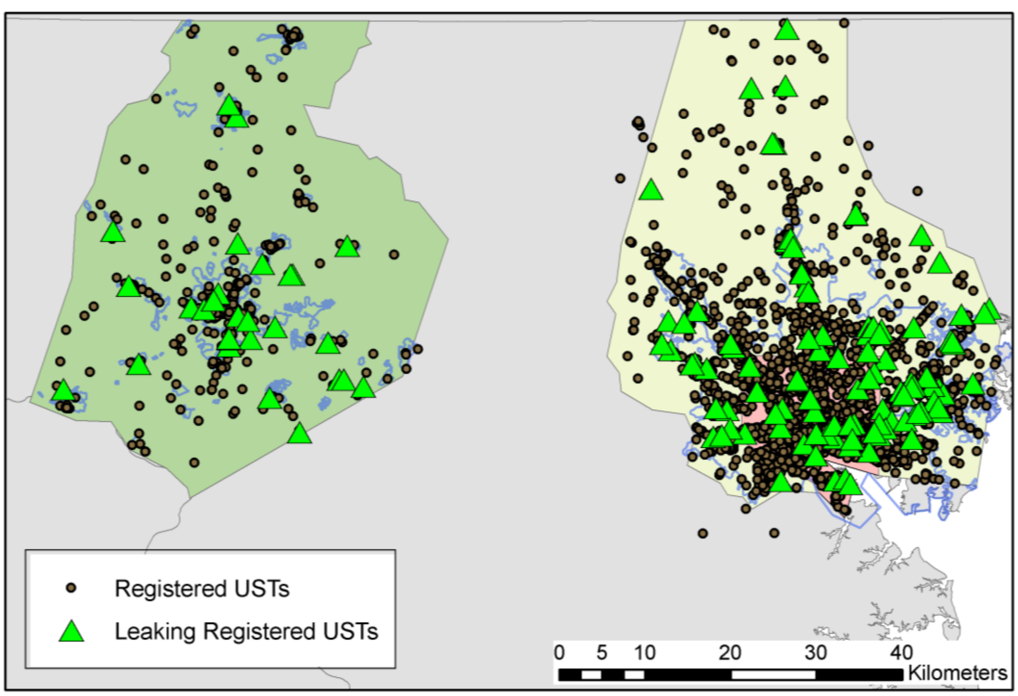


Figure 3. Leak Cases Opened in Each County by Year.

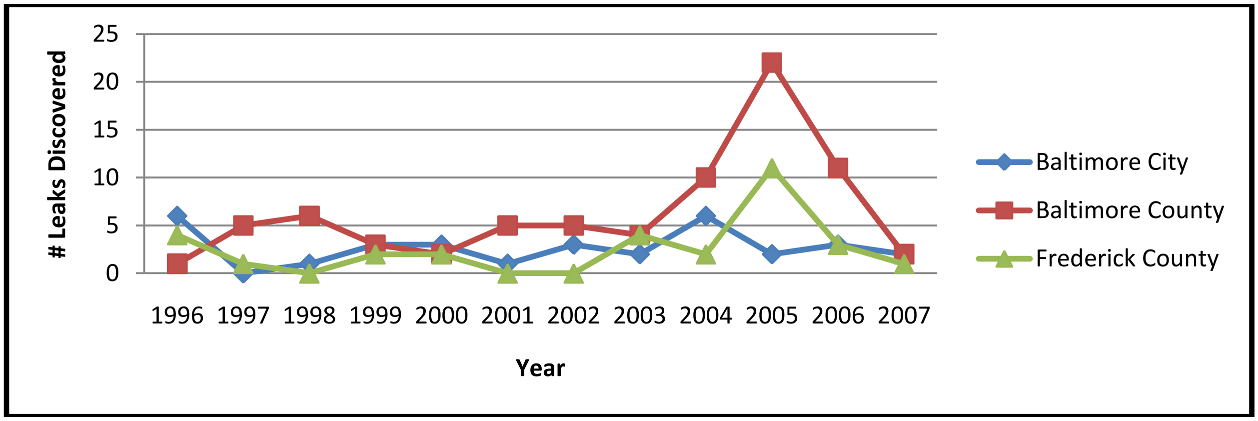


Figure 4. Number of Potable Well Tests (among 50 sales where testing occurred prior to sale)

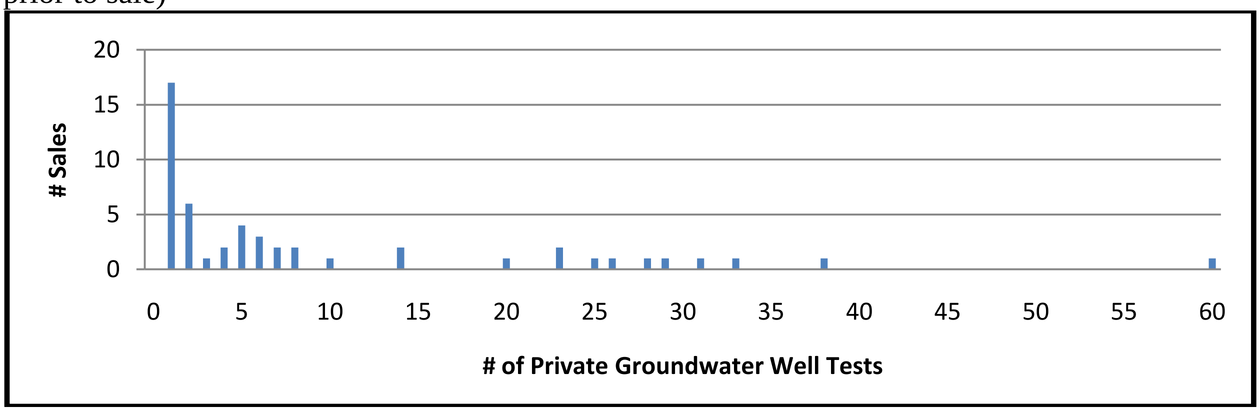


Figure 5. Sales Rate Trends by County.

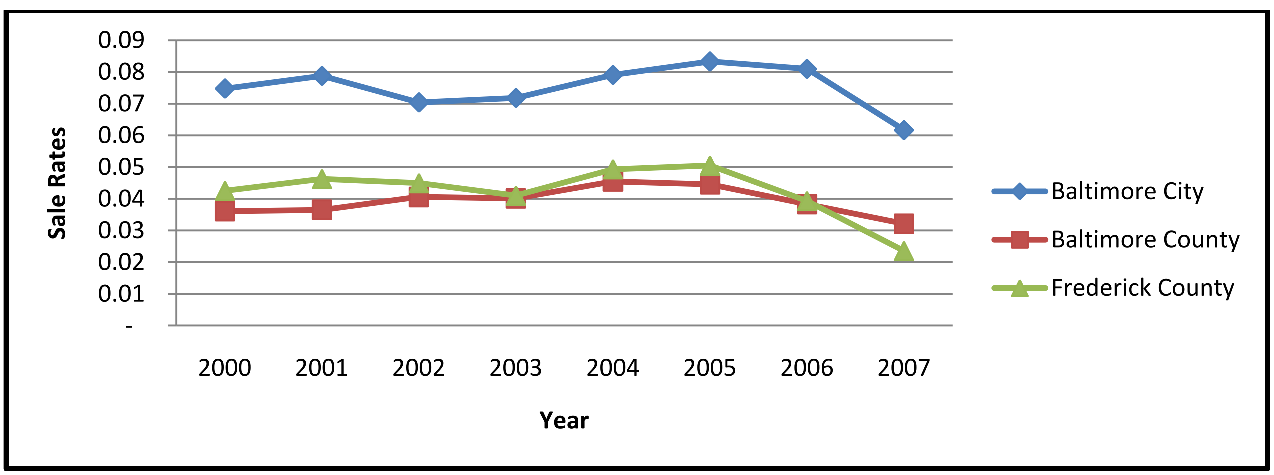
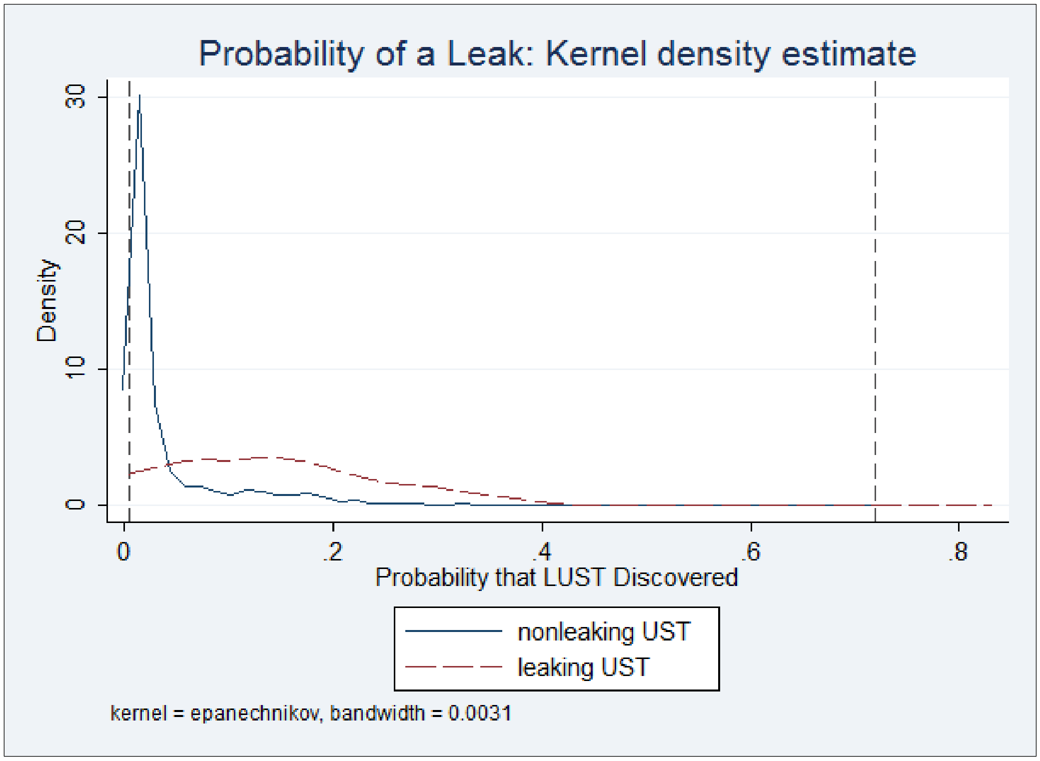


Figure 6. Kernel Density Estimate of the Probability that a Leak is Discovered at a UST Facility (from Model 13.B in Table 13).



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 Registered Underground Storage Tank Facilities by Type of Facility.†

	Baltimore City	Baltimore	Frederick	Total
Commercial	113	144	48	305
Gas Station	206	279	89	574
Industrial	240	135	46	421
Unknown	1003	937	276	2216
Total	1562	1495	459	3516

†The UST facilities classification listed here comes from the Maryland Department of Environment's inspection reports. This is the current use of the facility, as of May, 2009.

Table 3. 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 4. 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

Note:

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 5. 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 6. 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 7. Base Hedonic Price Regression Results for Entire Study Area (Baltimore City, Frederick, and Baltimore County).

VARIABLES	Model 7.A ln(price)	Model 7.B ln(price)	Model 7.C ln(price)	Model 7.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 County, and census tract for Baltimore City).

a. Repeat Sales Model.

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

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)	0.0337	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 8.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Table 9. Base Hedonic Price Regression Results for Baltimore 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)	-0.0269***	-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 9.D, where a nonzero correlation is allowed for the 7 nearest neighbors.

Table 10. Base Hedonic Price Regression Results for Frederick County.

VARIABLES	Model 10.A ln(price)	Model 10.B ln(price)	Model 10.C ln(price)	Model 10.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 10.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Table 11. Hedonic Price Results: Varying Baseline Effects by Type of UST Facility.

VARIABLES	Baltimore City Model 11.A	Baltimore County Model 11.B	Frederick County Model 11.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 County, and census tract for Baltimore City).

Table 12. Hedonic Price Results for Private Well v. Public Water Areas (Baltimore and Frederick Counties).

VARIABLES	Private Well Area Model 12.A	Public Water Area Model 12.B
Non-leaking UST within 500m (dummy)	0.0048	-0.0040
	(0.006)	(0.004)
LUST within 500m (dummy)	0.0102	-0.0317***
	(0.016)	(0.012)
× leak discovered (dummy)	0.0295	0.0421***
	(0.020)	(0.012)
× cleanup (dummy)	0.0271	0.0096
	(0.038)	(0.016)
× post-closure (dummy)	-0.0228	0.0157
	(0.023)	(0.012)
Neighborhood Characteristics:		
ln(Median Neighbor Price)	0.1180***	0.2450***
	(0.009)	(0.014)
Neighborhood Fixed Effects	Yes	Yes
(Number of Fixed Effects)	(227)	(527)
Home Characteristics:		
Home Structure × County	Yes	Yes
Home Location × County	Yes	Yes
Year and Quarter Dummies × County	Yes	Yes
Observations	23,890	86,433
R-squared	0.786	0.722

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

Note: Std errors are in parentheses. Errors are clustered by census block group.

Table 13. Quasi-Experimental Hedonic Results for Homes within 500 meters of UST.

	All Counties		Private Well Area	
VARIABLES	Model 13.A	Model 13.B	Model 13.C	Model 13.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 County, 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 14. Probit of Leak Discovery at UST Facility, Estimated Average Marginal Effects (all 3,516 registered facilities in study area).

VARIABLES	Model 14.A	Model 14.B	Model 14.C	Model 14.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	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 (dummy)	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:				
% pop in poverty				-0.006715
				(0.0324)
% housing vacant				0.026298
				(0.0378)
% housing own occupied				0.013834
				(0.0136)
median home value ($1000s)			0.000019	
			(0.0000)	
Log Likelihood	-463.366110	-459.292861	-459.196168	-458.358468

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

Table 15. Hedonic Price Results with Private Well Testing (only homes in private well areas).

VARIABLES (dep variable = ln(price))	All Homes Model 15.A	Within 500m of UST Model 15.B	Model 15.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.B).

Table 16. Hedonic Price Results with Private Well Tests: A Robustness Check (only homes in private well areas).

VARIABLES	All Homes Model 16.A	Within 500m of UST Model 16.B	 Model 16.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
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.B).

Table 17. Single Family Home Parcels by County and Water Source.

	Baltimore City	Baltimore	Frederick	Total
Public Water	29,990	113,956	20,930	164,876
Private Wells	-	25,776	21,416	47,192
Total	29,990	139,732	42,346	212,068

*Note: only sales used in sale probability model (see section VII).

Table 18. Number of Parcels and Sales by County and Year.

	2000	2001	2002	2003	2004	2005	2006	2007	Total
					Baltimore City County				
Not Sold	27,748	27,629	27,879	27,837	27,620	27,493	27,563	28,141	221,910
Sold	2,242	2,361	2,111	2,153	2,370	2,497	2,427	1,849	18,010
					Baltimore County				
Not Sold	134,691	134,631	134,065	134,126	133,383	133,507	134,382	135,246	1,074,031
Sold	5,041	5,101	5,667	5,606	6,349	6,225	5,350	4,486	43,825
					Frederick County				
Not Sold	40,546	40,387	40,443	40,609	40,257	40,208	40,682	41,350	324,482
Sold	1,800	1,959	1,903	1,737	2,089	2,138	1,664	996	14,286

*Note: only sales used in sale probability model (see section VII)

Table 19. Probit Results of Annual Probability of a Home Sale by County. Estimated Average Marginal Effects (dep variable sold=1 if home sold that year, 0 otherwise).

VARIABLES	Baltimore County Model 19.A	Frederick County Model 19.B	Baltimore City Model 19.C
# of USTs within 0-500 m	0.0003**	-0.0002	-0.0004***
	(0.000)	(0.000)	(0.000)
Non-leaking UST within 500m (dummy)	-0.0003	-0.0009	0.0021
	(0.001)	(0.001)	(0.002)
LUST within 500m (dummy)	-0.0023**	0.0037	0.0042
	(0.001)	(0.003)	(0.004)
× leak discovered (dummy)	0.0071***	-0.0010	-0.0008
	(0.002)	(0.003)	(0.005)
× cleanup (dummy)	-0.0026	-0.0095***	-0.0357***
	(0.003)	(0.004)	(0.013)
× post-closure (dummy)	0.0028*	0.0014	0.0084**
	(0.002)	(0.005)	(0.004)
Home Characteristics:			
Home Structure	Yes	Yes	Yes
Home Location	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	1,117,856	338,768	239,920
Log Likelihood	-183828.2091	-58077.5181	-63592.6930

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

Note: Std errors are in parentheses. Errors are clustered for same parcel over all years.

Table 20. Probability of a Sale Results by Public Water v. Private Well Areas, Estimated Average Marginal Effects† (Baltimore and Frederick Counties; dep variable sold=1 if home sold that year, 0 otherwise).

VARIABLES	Probit: Private Well Model 20.A	Probit: Public Water Model 20.B	FE Logit†: Public & Well Water Model 20.C
# of USTs within 0-500 m			
× Pvt Well (dummy)	0.0001		0.3613
	(0.001)		(0.463)
× Public Water (dummy)		0.0002*	0.0117
		(0.000)	(0.101)
Non-leaking UST within 500m			
× Pvt Well (dummy)	-0.0002		0.7500
	(0.001)		(0.987)
× Public Water (dummy)		-0.0000	0.0557
		(0.001)	(0.380)
LUST within 500m × Pvt Well	0.0004		-0.1892
	(0.003)		(1.413)
× leak discovered (dummy)	-0.0008		-0.0797
	(0.004)		(0.178)
× cleanup (dummy)	-0.0145***		-0.9723**
	(0.005)		(0.424)
× post-closure (dummy)	-0.0013		0.2392
	(0.004)		(0.229)
LUST within 500m × Public Water		-0.0013	-0.1467
		(0.001)	(0.529)
× leak discovered (dummy)		0.0072***	0.0898
		(0.002)	(0.059)
× cleanup (dummy)		-0.0024	-0.0686
		(0.002)	(0.102)
× post-closure (dummy)		0.0032*	0.1718**
		(0.002)	(0.073)
Home Characteristics:			
Home Structure	Yes	Yes	Yes
× County	Yes	Yes	No
Home Location	Yes	Yes	No
× County	Yes	Yes	No
Year Dummies × County	Yes	Yes	Yes
Observations	377,536	1,079,088	394,496 (49,312 homes)
Log Likelihood	-52980.2680	-188739.6612	-111489.0706

*** p<0.01, ** p<0.05, * p<0.1. Std errors are in parentheses. Errors are clustered for same parcel over all years.

† Average marginal effects displayed for Probits, but coefficients are presented for Fixed Effect

Logit.

Table 21. Probability of a Sale Results: “Low-” v. “High-End” Homes (only homes in private well area and within 500 meters of UST; dep variable sold=1 if home sold that year, 0 otherwise).

VARIABLES	Probit† Model 21.A[a]	FE Logit† Model 21.B[a]	FE Logit† Model 21.C[b]	FE Logit† Model 21.D[c]
# of USTs within 0-500 m	0.0005	0.3893	0.3916	0.3853
	(0.001)	(0.474)	(0.475)	(0.475)
LUST within 500m (dummies)	0.0003	-1.7519	-1.8435	-1.6161
	(0.003)	(1.519)	(1.553)	(1.447)
× leak discovered × low	-0.0011	-0.0984	-0.1188	-0.0729
	(0.004)	(0.197)	(0.198)	(0.224)
× cleanup × low	-0.0164***	-1.2857**	-1.1552*	-1.3564**
	(0.006)	(0.545)	(0.628)	(0.690)
× post-closure × low	-0.0019	0.1175	0.0913	0.1461
	(0.004)	(0.240)	(0.242)	(0.254)
× leak discovered × high	-0.0125	-0.0696	0.0641	-0.1327
	(0.008)	(0.519)	(0.411)	(0.254)
× cleanup × high	-0.0021	-0.2330	-0.8536	-0.7160
	(0.018)	(0.738)	(0.616)	(0.501)
× post-closure × high	0.0045	0.5084	0.7061	-0.0168
	(0.022)	(1.099)	(0.783)	(0.564)
Home Characteristics:				
Home Structure	Yes	Yes	Yes	Yes
× County	Yes	Yes	Yes	Yes
Home Location	Yes	No	No	No
× County	Yes	No	No	No
Year Dummies × County	Yes	Yes	Yes	Yes
Observations	76,616	17,590	17,590	17,590
Log Likelihood	-10968.2326	-4877.4668	-4877.7228	-4877.8393
Number of homes		2,199	2,199	2,199

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

Note: Std errors are in parentheses. Errors are clustered for same parcel over all years.

† Average marginal effects displayed for Probit model, but raw coefficients are presented for the Fixed Effect Logit models.

a. Low end homes defined by home quality rated as "low" or "average" by tax assessors, and higher end homes are those rated "good" or "high."
b. Low end homes defined as lower 75% assessed values for that year, and high end homes defined as highest 25% assessed values.
c. Low end homes defined as lower 50% assessed values for that year, and high end homes defined as highest 50%.

Chapter Appendix

Table A1. Base Hedonic Price Regression Results for Baltimore City: Full Results. (from models presented in table 8).

VARIABLES	Model 8.A ln(price)	Model 8.B ln(price)	Model 8.C ln(price)	Model 8.D ln(price)
Home Characteristics:				
logsqft	0.2534***	0.2900***	0.2801***	0.2525***
	(0.048)	(0.029)	(0.027)	(0.016)
ln(lot acreage)	0.1011***	0.1144***	0.1112***	0.1279***
	(0.021)	(0.014)	(0.013)	(0.009)
number of full baths	0.0315**	0.0341***	0.0324***	0.0339***
	(0.012)	(0.009)	(0.008)	(0.005)
number of half baths	0.1235***	0.0793***	0.0747***	0.0615***
	(0.014)	(0.008)	(0.007)	(0.007)
basement (dummy)	0.0400	0.0769***	0.0764***	0.0550***
	(0.034)	(0.024)	(0.021)	(0.017)
number of stories	-0.0558**	-0.0332**	-0.0326**	-0.0215*
	(0.026)	(0.016)	(0.016)	(0.011)
number of fireplaces	0.1450***	0.0691***	0.0692***	0.0467***
	(0.021)	(0.012)	(0.012)	(0.008)
number of fireplaces missing (dummy)	-0.0411	-0.0395**	-0.0234	-0.0251**
	(0.028)	(0.018)	(0.016)	(0.012)
porch size (square feet)	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
porch size missing (dummy)	0.0576***	0.0296**	0.0303**	0.0320**
	(0.016)	(0.013)	(0.013)	(0.014)
attached garage (dummy)	0.0889***	0.0442***	0.0358**	0.0240*
	(0.019)	(0.014)	(0.014)	(0.013)
low quality construction (dummy)	-0.0868	-0.3808***	-0.3692***	-0.3157***
	(0.150)	(0.121)	(0.114)	(0.117)
good quality construction (dummy)	0.8046***	0.2606***	0.2336***	0.2812***
	(0.073)	(0.063)	(0.056)	(0.021)
high quality construction (dummy)	1.1128***	0.5042***	0.4403***	0.5061***
	(0.096)	(0.072)	(0.067)	(0.089)
construction quality missing (dummy)	1.0951***	0.4702***	0.4270***	0.4910***
	(0.089)	(0.086)	(0.083)	(0.056)
age of home	-0.0092***	-0.0056***	-0.0053***	-0.0059***
	(0.002)	(0.001)	(0.001)	(0.001)
age of home^2	0.0000***	0.0000**	0.0000**	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)

Time of Sale Dummies:				
1997	-0.0378*	-0.0446***	-0.0337*	0.0523**
	(0.019)	(0.017)	(0.018)	(0.023)
1998	-0.0261	-0.0050	0.0206	0.0150
	(0.020)	(0.015)	(0.016)	(0.026)
1999	0.0082	0.0262	0.0497***	0.0125
	(0.021)	(0.017)	(0.018)	(0.026)
2000	0.0322	0.0450**	0.0580***	0.0332
	(0.024)	(0.022)	(0.022)	(0.022)
2001	-0.0016	0.0216	0.0310	0.0062
	(0.034)	(0.033)	(0.031)	(0.028)
2002	0.0655	0.0869**	0.0858**	0.0702***
	(0.040)	(0.037)	(0.033)	(0.025)
2003	0.1241***	0.1554***	0.1399***	0.1327***
	(0.044)	(0.039)	(0.034)	(0.027)
2004	0.2475***	0.2917***	0.2534***	0.2684***
	(0.047)	(0.040)	(0.035)	(0.026)
2005	0.4340***	0.4967***	0.4245***	0.4695***
	(0.036)	(0.031)	(0.026)	(0.026)
2006	0.5438***	0.6351***	0.5306***	0.6045***
	(0.034)	(0.029)	(0.029)	(0.026)
2007	0.5755***	0.6626***	0.5311***	0.6329***
	(0.039)	(0.026)	(0.029)	(0.026)
2nd quarter	0.0323***	0.0273***	0.0230***	0.0281***
	(0.010)	(0.008)	(0.008)	(0.009)
3rd quarter	0.1117***	0.0885***	0.0793***	0.0839***
	(0.010)	(0.008)	(0.008)	(0.008)
4th quarter	0.0984***	0.0947***	0.0806***	0.0915***
	(0.009)	(0.008)	(0.008)	('0.009)
Neighborhood Characteristics:				
nearest open space (km)	0.0407	0.0808**	0.0667**	0.1217***
	(0.050)	(0.040)	(0.033)	(0.047)
nearest commercial zone (km)	0.0457	0.0958**	0.0784**	0.2311***
	(0.052)	(0.040)	(0.032)	(0.055)
nearest major road (km)	0.0741	0.0925**	0.0800**	0.0342
	(0.052)	(0.041)	(0.035)	(0.052)
inverse distance to CBD (1/km)	0.3687			0.4361
	(0.301)			(0.318)
inverse distance to Washington, DC (1/km)	-95.8779***			
	(19.476)			
Census Tract Fixed Effects	No	Yes	Yes	No
(# of Fixed Effects)		(127)	(127)	

ln(Median Neighbor Price)			0.1780***	
			(0.032)	
median neighbor price missing (dummy)			2.0107***	
			(0.370)	
Spatial Lag				0.0198***
				(0.003)
Spatial Autocorrelation				0.7915***
				(0.008)
UST and Leak Variables:				
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	0.407
	(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)
Constant	11.4500***	9.5523***	7.5943***	9.4861***
	(0.476)	(0.268)	(0.520)	(0.129)
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 8.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Table A2. Base Hedonic Price Regression Results for Baltimore County: Full Results (from models presented in table 9).

VARIABLES	Model 9.A ln(price)	Model 9.B ln(price)	Model 9.C ln(price)	Model 9.D† ln(price)
Home Characteristics:				
ln(interior square footage)	0.3957***	0.3651***	0.3475***	0.3433***
	(0.015)	(0.010)	(0.009)	(0.005)
ln(lot acreage)	0.0779***	0.0746***	0.0714***	0.0909***
	(0.007)	(0.005)	(0.004)	(0.002)
number of full baths	0.0714***	0.0516***	0.0485***	0.0499***
	(0.005)	(0.003)	(0.002)	(0.002)
number of half baths	0.0601***	0.0412***	0.0404***	0.0412***
	(0.005)	(0.003)	(0.002)	(0.002)
basement (dummy)	0.0506***	0.0458***	0.0426***	0.0364***
	(0.007)	(0.004)	(0.004)	(0.002)
number of stories	-0.0341***	-0.0442***	-0.0405***	-0.0355***
	(0.009)	(0.006)	(0.005)	(0.003)
number of fireplaces	0.0781***	0.0412***	0.0419***	0.0368***
	(0.009)	(0.005)	(0.005)	(0.002)
number of fireplaces missing (dummy)	-0.0028	0.0001	0.0082	-0.0004
	(0.008)	(0.005)	(0.005)	(NA)
porch size (square feet)	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
porch size missing (dummy)	-0.0138*	-0.0015	-0.0053	0.0017***
	(0.007)	(0.005)	(0.005)	(0.001)
attached garage (dummy)	0.0646***	0.0352***	0.0315***	0.0356***
	(0.007)	(0.004)	(0.004)	(0.002)
low quality construction (dummy)	-0.1667***	-0.1602***	-0.1698***	-0.1708***
	(0.053)	(0.049)	(0.049)	(0.012)
good quality construction (dummy)	0.2714***	0.1497***	0.1163***	0.1898***
	(0.023)	(0.010)	(0.010)	(0.005)
high quality construction (dummy)	0.4275***	0.3168***	0.2648***	0.3389***
	(0.037)	(0.029)	(0.027)	(0.013)
construction quality missing (dummy)	-0.0617	-0.1393**	-0.1441**	-0.1082***
	(0.073)	(0.055)	(0.056)	(0.030)
age of home	-0.0050***	-0.0068***	-0.0063***	-0.0059***
	(0.000)	(0.000)	(0.000)	(0.000)
age of home^2	0.0000***	0.0000***	0.0000***	0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)

Time of Sale Dummies:				
1997	-0.0238***	-0.0225***	-0.0157***	-0.0304***
	(0.005)	(0.005)	(0.005)	(0.003)
1998	-0.0115*	-0.0100*	-0.0017	-0.0173***
	(0.006)	(0.006)	(0.005)	(0.004)
1999	0.0009	0.0055	0.0129***	-0.0002
	(0.005)	(0.004)	(0.004)	(NA)
2000	0.0239***	0.0302***	0.0361***	0.0215***
	(0.006)	(0.006)	(0.005)	(0.002)
2001	0.0793***	0.0843***	0.0849***	0.0748***
	(0.005)	(0.005)	(0.004)	(0.003)
2002	0.1180***	0.1302***	0.1232***	0.1203***
	(0.006)	(0.006)	(0.005)	(0.003)
2003	0.2169***	0.2332***	0.2117***	0.2237***
	(0.008)	(0.007)	(0.007)	(0.003)
2004	0.3339***	0.3584***	0.3213***	0.3505***
	(0.008)	(0.007)	(0.007)	(0.003)
2005	0.4980***	0.5257***	0.4658***	0.5214***
	(0.008)	(0.006)	(0.007)	(0.003)
2006	0.5644***	0.6045***	0.5183***	0.6001***
	(0.008)	(0.006)	(0.008)	(0.003)
2007	0.5499***	0.5821***	0.4725***	0.5777***
	(0.009)	(0.007)	(0.010)	(0.004)
2nd quarter	0.0393***	0.0329***	0.0317***	0.0344***
	(0.003)	(0.002)	(0.002)	(0.002)
3rd quarter	0.0826***	0.0716***	0.0676***	0.0711***
	(0.003)	(0.003)	(0.003)	(0.002)
4th quarter	0.0767***	0.0723***	0.0655***	0.0737***
	(0.003)	(0.003)	(0.003)	(0.002)
Neighborhood Characteristics:				
private groundwater well area (dummy)	-0.0404**	0.0350**	0.0128	0.0033***
	(0.016)	(0.015)	(0.013)	(0.001)
nearest open space (km)	0.0053	0.0007	0.0027	0.0076***
	(0.009)	(0.006)	(0.005)	(0.002)
nearest commercial zone (km)	0.0045	0.0193***	0.0090*	0.0335***
	(0.008)	(0.007)	(0.005)	(0.006)
nearest major road (km)	0.0080	0.0148**	0.0146***	0.0057***
	(0.007)	(0.006)	(0.005)	(0.001)
inverse distance to CBD (1/km)	-0.6629**			-1.3429***
	(0.274)			(0.125)
inverse distance to Washington, DC	-7.4203**			
(1/km)	(3.677)			

Block Group Fixed Effects	No	Yes	Yes	No
(# of Fixed Effects)		(479)	(479)	
ln(Median Neighbor Price)			0.2017***	
			(0.012)	
median neighbor price missing (dummy)			2.5179***	
			(0.149)	
Spatial Lag				0.0025***
				(0.000)
Spatial Autocorrelation				0.6821***
				(0.004)
UST and Leak Variables:				
Non-leaking UST within 500m (dummy)	-0.0269***	-0.0125***	-0.0076*	-0.0152***
	(0.009)	(0.004)	(0.004)	(0.000)
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)
Constant	9.2892***	9.4737***	7.1537***	9.6890***
	(0.112)	(0.077)	(0.161)	(0.035)
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 9.D, where a nonzero correlation is allowed for the 7 nearest neighbors.

†When estimating the spatial autoregressive model for Baltimore County (model 9.D), the maximum likelihood routine occasionally had difficulty numerically estimate the standard errors, hence missing standard errors are reported for some coefficients. I believe this may be a multicollinearity issue. The problem does not persist when some variables are excluded. This exclusion does not significantly change the estimated coefficients. Spatial autoregressive models were estimated using the “spdep” package in R.

Table A3. Base Hedonic Price Regression Results for Frederick County: Full Results (from models presented in table 10).

VARIABLES	Model 10.A ln(price)	Model 10.B ln(price)	Model 10.C ln(price)	Model 10.D ln(price)
Home Characteristics:				
ln(interior square footage)	0.4345***	0.3940***	0.3765***	0.3782***
	(0.015)	(0.011)	(0.010)	(0.004)
ln(lot acreage)	0.0775***	0.0815***	0.0812***	0.0851***
	(0.006)	(0.004)	(0.004)	(0.002)
number of full baths	0.0637***	0.0561***	0.0551***	0.0522***
	(0.005)	(0.003)	(0.003)	(0.002)
number of half baths	0.0548***	0.0430***	0.0416***	0.0391***
	(0.005)	(0.003)	(0.003)	(0.002)
basement (dummy)	0.0255***	0.0242***	0.0217***	0.0242***
	(0.007)	(0.005)	(0.005)	(0.003)
number of stories	-0.0727***	-0.0680***	-0.0641***	-0.0636***
	(0.008)	(0.007)	(0.006)	(0.003)
number of fireplaces	0.0502***	0.0388***	0.0376***	0.0359***
	(0.004)	(0.003)	(0.003)	(0.002)
number of fireplaces missing (dummy)	0.0194***	0.0233***	0.0261***	0.0201***
	(0.006)	(0.005)	(0.005)	(0.006)
porch size (square feet)	0.0001***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
porch size missing (dummy)	-0.0320***	-0.0192***	-0.0235***	-0.0131*
	(0.012)	(0.006)	(0.006)	(0.007)
attached garage (dummy)	0.0107**	0.0105***	0.0091***	0.0076***
	(0.005)	(0.003)	(0.003)	(0.001)
low quality construction (dummy)	-0.2431***	-0.2234***	-0.2260***	-0.2261***
	(0.033)	(0.029)	(0.029)	(0.011)
good quality construction (dummy)	0.1361***	0.1071***	0.0878***	0.1189***
	(0.015)	(0.010)	(0.009)	(0.003)
high quality construction (dummy)	0.2591***	0.2208***	0.1726***	0.2162***
	(0.024)	(0.026)	(0.024)	(0.055)
construction quality missing (dummy)	0.2674***	0.1817***	0.1645***	0.2143***
	(0.024)	(0.020)	(0.020)	(0.011)
age of home	-0.0045***	-0.0057***	-0.0053***	-0.0053***
	(0.001)	(0.000)	(0.000)	(0.000)
age of home^2	0.0000***	0.0000***	0.0000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)

Time of Sale Dummies:				
1997	-0.0075	-0.0081*	-0.0086*	0.0095
	(0.005)	(0.005)	(0.005)	(0.008)
1998	-0.0070	-0.0078*	-0.0069	-0.0084**
	(0.004)	(0.004)	(0.004)	(0.004)
1999	0.0173***	0.0204***	0.0198***	0.0206***
	(0.006)	(0.005)	(0.005)	(0.006)
2000	0.0246***	0.0316***	0.0303***	0.0307***
	(0.006)	(0.005)	(0.005)	(0.004)
2001	0.0909***	0.0957***	0.0900***	0.0951***
	(0.009)	(0.006)	(0.006)	(0.004)
2002	0.1785***	0.1847***	0.1714***	0.1838***
	(0.009)	(0.006)	(0.006)	(0.005)
2003	0.2936***	0.3026***	0.2794***	0.3041***
	(0.011)	(0.006)	(0.006)	(0.006)
2004	0.4391***	0.4544***	0.4153***	0.4542***
	(0.010)	(0.007)	(0.007)	(0.005)
2005	0.5900***	0.6046***	0.5451***	0.6062***
	(0.010)	(0.006)	(0.008)	(0.005)
2006	0.6309***	0.6474***	0.5709***	0.6492***
	(0.011)	(0.007)	(0.010)	(0.005)
2007	0.5801***	0.5962***	0.5114***	0.5976***
	(0.010)	(0.008)	(0.011)	(0.006)
2nd quarter	0.0269***	0.0282***	0.0264***	0.0281***
	(0.003)	(0.003)	(0.003)	(0.002)
3rd quarter	0.0498***	0.0506***	0.0466***	0.0493***
	(0.003)	(0.003)	(0.003)	(0.002)
4th quarter	0.0583***	0.0609***	0.0551***	0.0624***
	(0.003)	(0.003)	(0.003)	(0.003)
Neighborhood Characteristics:				
private groundwater well area (dummy)	-0.0267**	-0.0391***	-0.0400***	-0.0429***
	(0.010)	(0.010)	(0.009)	(0.005)
nearest open space (km)	0.0022	0.0027	0.0007	0.0013
	(0.003)	(0.004)	(0.003)	(0.001)
nearest commercial zone (km)	0.0040	0.0048	0.0024	-0.0113
	(0.005)	(0.005)	(0.004)	(0.008)
nearest major road (km)	0.0070	-0.0024	-0.0000	0.0077
	(0.005)	(0.004)	(0.003)	(0.006)
inverse distance to CBD (1/km)	0.1041**			0.0650***
	(0.050)			(0.017)
inverse distance to Washington, DC (1/km)	0.0002***			
	(0.000)			

Block Group Fixed Effects	No	Yes	Yes	No
(# of Fixed Effects)		(127)	(127)	
ln(Median Neighbor Price)			0.1362***	
			(0.013)	
median neighbor price missing (dummy)			1.6643***	
			(0.154)	
Spatial Lag				0.0013***
				(0.000)
Spatial Autocorrelation				0.7604***
				(0.007)
UST and Leak Variables:				
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)
Constant	9.0084***	9.3805***	7.8362***	9.4684***
	(0.107)	(0.078)	(0.166)	(0.030)
Observations	34,442	34,442	34,442	34,451
R-squared	0.878	0.863	0.867	
Log Likelihood				-18,568.870

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Note: Std errors are in parentheses. Errors are clustered by census block group, except in model 10.D, where a nonzero correlation is allowed for the 15 nearest neighbors.

Chapter 3: The Impacts of Pollution, Exposure Pathways, and Health Risks on Home Values: A Stated Preference Analysis

By: Dennis Guignet

I. Introduction

Hedonic property value methods are an attractive non-market valuation technique because welfare estimates are inferred from revealed behavior, and in theory, all components of a welfare change are capitalized in home prices, as long as the amenity or disamenity of interest is sufficiently local.[49] In practice, however, hedonic models are susceptible to omitted variable bias and multicollinearity issues (Bockstael and McConnell, 2006). Even more important, in hedonic studies researchers are often forced to make assumptions regarding the public's awareness and perceptions of the health and environmental risks being studied, and how the buyers and sellers in the housing market measure these risks. Such assumptions are often necessary, but rarely tested; if proven invalid, we may in fact be incorrectly inferring welfare effects from changes in property values.

Stated preference approaches provide a viable way to get around multicollinearity and omitted variable issues. Furthermore, respondents in stated preference studies are supplied with information and specific scenarios, based on the same measure of environmental quality used by the researcher. At least in theory, well-executed stated preference methods provide an opportunity to examine how home values are affected when we *know* exactly what is being valued, and are not

[49] An amenity or disamenity is considered sufficiently local when it only affects a small number of homes in the housing market, and so there is no shift in the equilibrium hedonic price surface (Palmquist, 2005; Bockstael and McConnell, 2006).

forced to make such assumptions as in hedonic models. These advantages stem from the fact that stated preference questions are framed within hypothetical scenarios, which is a potential disadvantage of the approach (see Freeman, 1999, pg. 176).

Only a handful of analyses, however, have attempted to compare hedonics and analogous stated preference studies in the context of home values and environmental disamenities (Jenkins-Smith, 2002; Chattopadhyay et al., 2005; Simons and Winson-Geideman, 2005; Phaneuf et al., 2010). These studies all convey the environmental good by qualitatively outlining a scenario.[50] Alternatively, one could convey the severity of an environmental disamenity using quantitative measures, such as presenting respondents with the objective risks (e.g., an X% probability of some adverse health or environmental outcome), or by providing an actual concentration or level of pollution (e.g., X parts-per-billion), which is the approach I undertake in this analysis.

The goal of this study is to examine how people believe home values adjust to reflect pollution levels at the home or other homes in the neighborhood. To my knowledge this paper is the first stated preference analysis examining changes in property values using a quantitative measure of pollution. I wish to answer three research questions. First, do people believe home values will decrease due to a local environmental disamenity even if the home itself is not polluted, or if an exposure pathway is not present? Second, is this decline more pronounced when the home itself is actually polluted, and is the loss in value greater for higher levels of pollution?

[50] Earnhart (2001, 2002) combined a hedonic and conjoint choice study to examine how property values are affected by various land and water based amenities. He took a slightly different approach in that respondents were shown photographs of these amenities when choosing among hypothetical homes.

Third, is this response in home values to contamination levels symmetric just above and below the regulatory standard?

To answer these questions I use a survey-based approach, and incorporate several experimental treatments into a questionnaire on leaking underground storage tanks (LUSTs) and groundwater pollution.[51] Respondents are asked to assess the price of several homes, each of which are randomly assigned a hypothetical level of benzene contamination in the groundwater. Benzene is a petroleum by-product and proven carcinogen.

Participants are also assigned at random to one of three scenarios, where the homes (i) rely on private groundwater wells for potable water; (ii) are connected to the public water system; or (iii) rely on private groundwater wells for drinking, and a filter is installed that eliminates all pollution, making the water safe for consumption. The information provided to the respondents is the same as the Maryland Department of Environment's Oil Control Program provides to households whose groundwater wells are tested for petroleum pollution.

The questionnaire was self-administered by a convenience sample of Maryland residents in April and October, 2010. I care for the relative effect of the survey treatments, and not the absolute magnitude of the effects on housing values.

I find that even if a home's groundwater is not contaminated, and even if there is no exposure pathway, respondents believe home prices will decline by 18% to 24% just because the home is close to a LUST. Prices decline more if higher levels of groundwater pollution are found at the home. This effect is not symmetric just below

[51] In chapter 2 of this dissertation, I discuss details on leaking underground storage tanks and the environmental regulations (see section II), as well as the few hedonic studies examining how LUSTs affect on home prices (see section II.D).

and above the 5 parts-per-billion (ppb) regulatory standard: the decline in home prices is much more pronounced at contamination levels above the standard. Individuals likely use the regulatory standard as a ceiling for what is considered “safe” (Smith et al., 1990; Johnson and Chess, 2003; Johnson, 2008), and so when this was exceeded they reported much more of a decline in home prices.

The decline in reported home prices is more pronounced when homes rely on private groundwater wells (and thus a clear exposure pathway is present), but this effect is not statistically different from responses under the scenario where the homes are connected to the public water system (and thus an exposure pathway is not present). However, if a filter is installed and the respondents are explicitly told that it eliminates all the pollution and health risks, then groundwater contamination generally has a small and statistically insignificant effect on home prices. Nonetheless, the initial 18% depreciation just because a LUST site is in the neighborhood remains.

The remainder of this paper is organized as follows. In section II, I review past stated preference studies that are of particular relevance to this analysis. I then outline the study design and empirical model in section III, and provide an overview of the survey data in section IV. The results are presented in section V. Section VI concludes and discusses future research directions.

II. Literature Review: Stated Preference Methods

Stated preference methods are a possible approach for estimating the value of environmental goods and services. Respondents are presented with hypothetical circumstances and asked questions in order to elicit their value for an environmental good. Stated preference methods have been applied to a variety of environmental contexts, including air quality (e.g., Carlsson and Johansson-Stenman, 2000; Wang et al., 2006), water quality (e.g., Hanley et al., 2006; Machado and Mourato, 2002; Lipton, 2004), contaminated sites (e.g., Chattopadhyay et al., 2005; Tonin et al., 2009), and health risks (e.g., Alberini et al., 2006a; Alberini and Ščasný, 2011).

II.A. Groundwater Contamination

However, relatively few stated preference studies have focused on groundwater quality.[52] Boyle et al. (1994) conduct a meta-analysis, identifying eight contingent valuation studies. This was later revisited by Poe et al. (2001), who identify 13 studies, all of which report a positive mean willingness-to-pay (WTP) for improved groundwater quality, but the magnitude of the WTP estimates varies substantially. Despite the wide range of WTP estimates, definitions of groundwater contamination, and valuation approaches, the meta-analyses suggest that WTP values do systematically vary in ways consistent with economic theory.

Stevens et al. (1997) estimate the public's WTP for groundwater protection via an aquifer protection district, a public water treatment plant, a private in-home water filter, and bottled water. In their survey they ask residents in 56 western Massachusetts towns to rate several water protection programs with varying attributes. WTP is estimated using a traditional ratings model, a ratings difference specification, and a dichotomous choice model. Depending on the model they find the average households' WTP for an in-home water filter is $33 to $431 (2010$) per

[52] Bergstrom et al. (2001) present a collection of most of these studies.

year, for 10 years.[53] In comparison, they find the average household is willing to pay $22 to $260 for a water treatment plant, $48 to $463 for an aquifer protection district, and only $4 to $103 for a program that simply provides them with bottled water. The dichotomous choice specification yielded the lowest WTP estimates. Stevens et al. conclude (as is implicit in the wide range of values reported above) that WTP estimates are very sensitive to model specification.

II.B. Contaminated Sites and Health Risks

Reduced health risks are likely one of the largest components of the benefits from cleaning up soil and groundwater pollution from a contaminated site, such as a LUST. There have been many stated preference studies that explicitly estimate the value of reduced mortality and morbidity risks associated with different diseases, sources, and risk reduction vehicles.[54]

To my knowledge there are only two stated preference studies valuing health risk reductions from the cleanup of contaminated sites. Alberini et al. (2007) conduct a choice experiment, where respondents choose between variants of a hypothetical public program to clean up severely contaminated sites in Italy. The attributes of the alternative programs are (i) the number of lives saved (i.e., the annual risk reduction), (ii) the size of the potentially affected population, (iii) how soon the risk reduction would be experienced (latency), (iv) the number of years over which the risk reduction would be experienced (permanence), and (v) the cost. They find that people

[53] I converted Stevens et al.'s (1997) estimates to 2010 dollars using the US City average consumer price index (US Dept of Labor, ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt, accessed March 14, 2010).
[54] Recent examples include (but are not limited to) Alberini and Chiabai (2007), Alberini et al. (2006a, 2006b), Itaoka et al. (2006), and Tsuge et al. (2005).

are willing to pay more for more permanent cleanup technologies, but respondents also consider the cost when making this decision. People are also willing to pay more for immediate risk reductions, and WTP systematically varies based on characteristics of the respondent, and their familiarity and concerns about contaminated sites, pollutants, and the perceived effectiveness of government remediation programs.

Tonin et al. (2009) survey residents living near a highly contaminated industrial complex in Marghera, Italy. Respondents were asked to choose between hypothetical remediation and reuse programs targeted at other contaminated sites, not the Marghera site itself. The alternative programs varied in terms of the (i) initial contamination level at the targeted sites, (ii) number of cancer cases avoided due to cleanup (i.e., reduction in cancer risks), (iii) proposed reuse of the site (e.g., remain idle, industrial, residential, and recreational), and (iv) a one-time cost to the respondent. The sample was selected from residents at specified distances from the Marghera site to examine whether people living closest to the site have a higher or lower WTP for a cancer risk reduction from cleanup.

Despite the possibility that people who opt to live near the Marghera site may be more risk-tolerant, Tonin et al. (2009) find that they have a higher WTP for a reduction in cancer risks, even if the reduction is experienced by people living near a different contaminated site. Respondents' WTP also varies based on their opinions of cleanup priorities, and is higher among higher income households.

II.C. Contaminated Sites and Home Values

Both Alberini et al. (2007) and Tonin et al. (2009) infer the benefits of cleaning up contaminated sites from choice experiments in the context of a public good, specifically a regulatory cleanup program. A related strand of stated preference literature estimates the welfare effects of contaminated sites by focusing on the choice of a private good, namely one's home. This is done largely for comparison to the large body of hedonic property value studies that estimate the benefits of cleaning up contaminated sites.[55]

Chattopadhyay et al. (2005) estimate a hedonic property value model of homes near Waukegan Harbor, a Superfund site on Lake Michigan that is contaminated by polychlorinated biphenyls (PCBs). In the hedonic model the environmental disamenity is measured by distance to the harbor. They also conduct a survey asking respondents to choose between hypothetical variations of their home that differ in terms of lot and house size, school quality, amount of public space devoted to nature and recreation, cost of the home, and the environmental condition of the harbor. The latter is described qualitatively to the respondent in very general terms.

Four different pollution levels or scenarios are presented (additional pollution, no change, partial clean-up, and full clean-up). Each is briefly described in terms of more or less pollution relative to the status quo, whether full or partial cleanup takes place, whether regulatory cleanup goals are met, and whether the conditions are considered safe to the health of recreationists and wildlife. Even though the measure of the disamenity used in the hedonic models (distance to harbor) is not directly

[55] See Boyle and Kiel (2001) for a review of hedonic studies organized by environmental disamenity. Farber (1998) and Jackson (2001) review the hedonic literature on undesirable land uses, especially Superfund sites. As discussed in chapter 2, there are relatively few revealed preference studies on house prices and groundwater contamination (Malone and Barrows, 1990; Page and Rabinowitz, 1993; Dotzour, 1997; Boyle et al., 2010), and specifically on leaking USTs (Simons et al., 1997, 1999; Zabel and Guignet, 2011).

comparable to the qualitative measure in the stated preference counterpart, Chattopadhyay et al. conclude that the aggregate benefit estimates of cleanup are similar across the two methods.

Focusing on the benefits of cleaning up pollution in the Buffalo River, in Buffalo, NY, Phaneuf et al. (2010) take a similar approach to Chattopadhyay et al. (2005). In their survey design Phaneuf et al. also vary distance of a home to the river, which is directly comparable to a parallel hedonic study. They pursue a general method of moments (GMM) procedure to simultaneously estimate welfare effects using both stated preference data and actual housing transactions.

Jenkins-Smith et al. (2002) examine how real estate disclosure requirements about lead, cadmium, and zinc contamination from an actual lead smelter in Corpus Christi, Texas, affect home sale prices. The survey was implemented on a sample of residents within one mile of the smelter. Respondents were asked whether they would buy (or sell) a hypothetical home, where the price of each home was varied as part of the study design. Respondents were assigned to a treatment or control group, where the former received additional disclosure information stating that homes in the neighborhood were previously contaminated but have since been cleaned up, and pollution levels no longer exceed the regulatory safety standards.

The study suggests a significant discount in buyers' bids (30.5%) when information about past contamination is disclosed. Individuals were also willing to sell these hypothetical homes at a similar discount. Moreover, about half of the respondents who received the additional pollution disclosure would not buy the home at any price, even though the pollution was cleaned up and levels were below the regulatory safety standards.

Simons and Winson-Geideman (2005) conducted a contingent valuation survey in eight States (Kentucky, Pennsylvania, Ohio, Alabama, Illinois, South Carolina, West Virginia, and Texas). To my knowledge, this is the only other stated preference study specifically on LUSTs. Respondents were asked to bid on a hypothetical home near a gas station, where a leak had previously occurred. They were told that the leaking tanks were to be fixed, but no cleanup was undertaken. Respondents were assigned at random to scenarios that qualitatively described different degrees of contamination at the home. Overall, Simons and Winson-Geideman find that (i) LUST activity reduces the likelihood that a respondent will bid on a home, (ii) bids are on average 31% lower when the groundwater is contaminated, and (iii) this depreciation was consistent across states, ranging from 25-33%.

All four of the above stated preference studies examining the effects of pollution on home values convey the severity of the disamenity using qualitative measures or scenarios (Chattopadhyay et al., 2005; Jenkins-Smith et al., 2002; and Simons and Winson-Geideman, 2005). Although it may be easier for respondents to relate to such measures, these scenarios are subjective, and are not always comparable to hedonic studies of similar types of environmental disamenities. In contrast, in this paper I utilize a quantitative measure of pollution, namely pollutant concentrations (e.g., parts-per-billion) in residential groundwater wells. The information provided to respondents in this questionnaire mimics that provided by environmental regulators to households in the same study area who are actually affected by LUSTs (see section II.C in chapter 2).

III. Study Design and Empirical Model

III.A Study Design

The objective of this study is to examine how people believe home values will respond to information regarding groundwater pollution levels beneath the home. I set out to investigate three main research questions. First, do people believe that a localized environmental disamenity affects home values, even when there is no pollution at the home itself, or when an exposure pathway to the contaminants is not present? Second, is this decline more pronounced at higher levels of groundwater pollution? Third, is this response in home values symmetric around the regulatory standard?

To examine these questions I devise a study design with several experimental treatments. I chose to frame the study around groundwater pollution from leaking underground storage tanks (LUSTs) because (i) they are a localized disamenity, (ii) residents are often the primary party whose welfare is affected, and (iii) in theory these welfare changes should be capitalized in house prices. Focusing on LUSTs also provides a natural and realistic context to invoke the experimental treatments for answering my research questions, while at the same time mimicking information provided to homeowners who are actually affected by leaking tanks in Maryland (the State where the survey is implemented).

I posit that a leak at a nearby gas station and the subsequent groundwater pollution will change individuals' perceptions of health and environmental risks, and in turn, cause nearby home values to decrease. I first show respondents the aerial photo of a generic suburban neighborhood in Maryland with a gas station. The respondents are then shown a second aerial photo of the same neighborhood, with annotations identifying a gas station with a LUST (figure 1). In earlier focus groups we found that people responded well to these aerial photos and were immediately capable of telling if this neighborhood was similar to their own (Alberini and Guignet, 2010),

As shown in figure 1, three homes (home A, B, and C) are presented to the respondent with varying levels of groundwater pollution. I chose these homes because they are roughly the same distance from the LUST site. Although the neighborhood and gas station are real, the leak and groundwater pollution levels are hypothetical. The groundwater pollution at Home A is always specified as 0 parts-per-billion (ppb). This serves as a baseline for comparison to home price responses to homes B and C, which I randomly assign benzene pollution levels of 0, 1, 4, 6, or 9 ppb. These values were chosen because the regulatory standard for benzene is 5 ppb, and I want to examine if people believe prices are affected differently at levels above and below this standard.

I create three variants of this scenario to investigate whether respondents believe house prices will be impacted differently by pollution when health risks are present. The first is the *Private Well* scenario, which posits that a clear exposure pathway to the contaminated groundwater is present. Respondents randomly assigned to this scenario are shown the text presented in table 1, along with a variant of the aerial photo (figure 1). The second variant is the *Public Water* scenario, where respondents are told that the homes are "served by the public water system, which gets its water from a distant reservoir." Since the water supply to the home does not come from the groundwater directly beneath it, there is no exposure pathway to the contaminated groundwater. In this case respondents should infer that there are no health risks, despite the benzene pollution.

The third version is the *Well with Filter* scenario, where respondents are told that the homes rely on private groundwater wells, but a filter is installed that removes the pollution before the water is consumed, thus eliminating any health risks. The specific text is displayed in table 1. As shown in figure 2, the aerial photo further conveys that all pollution is eliminated in the *Well with Filter* scenario.

The respondents are then asked the open-ended valuation question, "How much do you think each of these homes will sell for after this leak?" In other words, I simply ask respondents for their third-party assessment of the post-leak sale price of homes A, B, and C. This is a unique approach compared to previous stated preference studies on home values and environmental disamenities, which put respondents in the role of the home buyer or seller (Chattopadhyay et al., 2005; Jenkins-Smith et al., 2002; and Simons and Winson-Geideman, 2005). I take this third party assessment approach in order to minimize hypothetical biases that may arise due to respondents taking an unrealistic moral or socially "correct" stance (Kahneman and Tversky, 1979; Fisher, 1983; Epley and Dunning, 2000).

III.B. Is this the Appropriate Valuation Scenario?

The development of this questionnaire benefited from a series of four focus groups (consisting of 8 to 9 people) and four 3-on-1 interviews in Fall 2009 and Spring 2010 (Alberini and Guignet, 2010). Participants were recruited from residents of urban and suburban Maryland, and mirrored the population in terms of gender, education, and income. We examined the feasibility of a stated preference instrument to estimate the benefits of cleaning up and preventing leaks from underground storage tanks.

We found that when participants are asked questions from the perspective of a homebuyer/seller, they often took a firm moral stance, deeming a property unsellable, or stating they would not purchase the property for any price, even if the home itself is not contaminated. However, in chapter 2 of this dissertation and in a parallel hedonic study we find that homes near LUST sites are sold on the market (Zabel and Guignet, 2010). I believe that focus group participants in these hypothetical exercises were adopting stances to reflect what they consider morally or socially “correct.” Alberini and Guignet (2010) found that when questions are framed in a more generic fashion (i.e., not putting participants explicitly in the role of a homebuyer or seller) respondents are more willing to make tradeoffs between the price of a home and pollution levels.

This type of response is well documented in the psychology and sociology literature. Kahneman and Tversky (1979) find that when people predict behavior in situations where they are intensely involved they over-weigh certain types of information, which in turn biases their predictions. Others have also found that people tend to make unrealistic predictions about their own behavior in situations with a moral or socially normative component (e.g., Fisher, 1983; Epley and Dunning, 2000). Instead of asking survey respondents to answer questions predicting their own behavior in a hypothetical situation, framing the question in terms of forecasting others' behavior (or in my case, the overall housing market's behavior) will reduce such biases and more accurately reflect actual behavior (Kahneman and Tversky, 1979; Fisher, 1983; Epley and Dunning, 2000).

Framing valuation questions in terms of predicting others' behavior has only recently emerged in the economics literature, and has been referred to as *inferred valuation*. Lusk and Norwood (2009a, 2009b) and Yadav et al. (2010) find evidence supporting the intuition behind the inferred valuation approach, which is that in stating how much someone else values a good, the respondent is in fact projecting their own valuation while at the same time reducing hypothetical biases arising from social pressures or inner-moral conflicts associated with the normative nature of the good.

In this dissertation chapter I take an approach similar to inferred valuation, and simply ask respondents how much a home would sell for after contamination. I posit that this third-party assessment of the sale price reflects respondents' WTP to prevent or cleanup the pollution, while at the same time reducing any hypothetical biases associated with the highly normative component of buying a home with polluted groundwater.

III.C. Survey Structure

The survey consists of five sections.[56] I briefly describe each section here. Section A asks respondents about their current home, county of residence, how long they lived there, the type of neighborhood they live in (rural, suburban, or urban), and whether they own or rent their home. Section B inquires about the source of drinking water at their home, and experience with water quality testing and issues. The information gathered in these two sections will allow me to examine whether the effect of pollution on reported housing prices depends on the respondent's home and neighborhood, and experience with private groundwater wells and water quality.

Section C poses several questions regarding respondents' familiarity with common water pollutants, the units of measurement (parts-per-billion), and leaking underground storage tanks. This allows me to examine whether the effects of pollution on announced home prices varies with familiarity of benzene and the pollution source. After these inquiries respondents are told that underground storage tanks store petroleum, are commonly found at gas stations, occasionally leak due to rusting and cracks, and that benzene is a common pollutant from such leaks. I provide some basic background information, including that 1) water pollution concentrations are measured in parts-per-billion (ppb), 2) the regulatory standard for benzene is set at five parts-per-billion (ppb) in order to "to protect human health with a wide margin of safety," and that 3) benzene is a carcinogen. Similar information is provided by the Maryland Department of Environment (MDE) to residents who are actually affected by LUSTs and whose groundwater is tested for petroleum pollution. Providing the

[56] A complete version of the survey is available in Appendix B.

regulatory standard allows me to examine whether the effects of pollution on house prices is symmetric around the standard.

Section D of the questionnaire presents respondents with the original unaltered aerial photo of the neighborhood shown in figure 1. Respondents are asked to rate how similar this neighborhood is to their own on a 1 to 5 scale (where 1 = very different from my neighborhood, 5 = very similar to my neighborhood). They are told that each of the homes in the neighborhood is worth $400,000, on average. I then pose that a leak has occurred at a nearby gas station, and respondents are asked how much each of the three homes would sell for (see section III.A).

Section E concludes the questionnaire with socio-demographic questions. I inquire about family status, annual household income, age, education, and whether the respondent has bought or sold a home, or has been actively looking to do so, within the last 5 years. The latter question is to examine whether peoples' beliefs in how house prices respond to pollution differ depending on recent experience in the housing market.

III.D. The Model

Each respondent is asked to evaluate the post-leak sale price, denoted p_{hi}^1, for three different homes, h=*A*,*B*,*C*. I posit that their assessment of the price after the leak depends on the environmental and risk conditions imposed in the survey, the respondent's prior knowledge and preferences, and their belief of the pre-leak price p_{hi}^0. Formally,

$$p_{hi}^1 = p_{hi}^0 - D(\boldsymbol{T}_i, \boldsymbol{ppb}_{hi}, \boldsymbol{k}_i, \boldsymbol{x}_i) \quad (1)$$

where i denotes the respondent, $D(\cdot)$ is the damage or loss in price due to the LUST and groundwater pollution.[57] This loss is a function of the benzene pollution in the groundwater beneath the home ($\boldsymbol{ppb}_{hi}$), and the exposure pathway, which is specified by the experimental treatment ($\boldsymbol{T}_i$): (i) *Public Water*, (ii) *Private Well*, or (iii) *Well with Filter*. The loss in price may also depend on the respondent's prior knowledge and experience with LUSTs, groundwater, and water pollution, denoted $\boldsymbol{k}_i$, as well as their preferences, which I proxy with a vector of socio-economic characteristics ($\boldsymbol{x}_i$).

I do not observe respondents' beliefs regarding the pre-leak price of these homes (p_{hi}^0), but they are told that prior to the leak the homes are worth \$400,000 on average.[58] I posit that respondents' perceived pre-leak home prices depend on the pre-leak conditions specified in the survey, as well as their preferences and past experiences. Let $\bar{p}^0 = \$400{,}000$ denote the average neighborhood home price. Assuming a linear form for p_{hi}^1, equation (1) can be re-written as:

$$p_{hi}^1 = \gamma_0 \bar{p}^0 + \boldsymbol{T}_i \boldsymbol{\gamma}_1 + \boldsymbol{k}_i \boldsymbol{\gamma}_2 + \boldsymbol{x}_i \boldsymbol{\gamma}_3 - D(\boldsymbol{T}_i, \boldsymbol{ppb}_{hi}, \boldsymbol{k}_i, \boldsymbol{x}_i) + \varepsilon_{hi}. \qquad (2)$$

where γ_0, γ_1, γ_2, and γ_3 are unknown parameters, and ε_{hi} is an assumed normally distributed disturbance, which is allowed to be correlated for each of respondent *i's* responses for homes *h=A,B,* and *C*.

I then assume a linear form for $D(\cdot)$ and estimate the reduced-form econometric equation:

$$p_{hi}^1 = \boldsymbol{T}_i \boldsymbol{\beta}_0 + (\boldsymbol{T}_i \otimes \boldsymbol{ppb}_{\boldsymbol{hi}}) \boldsymbol{\beta}_1 + \boldsymbol{k}_i \boldsymbol{\beta}_2 + \boldsymbol{x}_i \boldsymbol{\beta}_3 + \varepsilon_{hi} \qquad (3)$$

[57] This notation is sufficiently general to allow for the damage to be negative (i.e., for the home to appreciate with pollution).

[58] To account for unobserved deviations in pre-leak prices from this \$400,000 average, in my econometric analysis I include fixed effects for each home.

where $\boldsymbol{T}_i$ is a 1×3 vector of indicator variables equal to one if the respondent received a variant of the survey corresponding to that experimental treatment, and zero otherwise. The 1×4 vector of indicator variables $\boldsymbol{ppb}_{hi}$ denotes the randomly assigned pollution level at home *h* (1, 4, 6, or 9 ppb).[59] The dummy variables corresponding to these four pollution levels equal one if that is the assigned concentration, and zero otherwise. The vector $\boldsymbol{k}_i$ represents the respondent's prior knowledge and familiarity, which may affect their perceptions of the environmental and health risks posed by LUSTs, and therefore how they believe home prices will change.

The coefficients to be estimated are $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$. The 3×1 vector $\boldsymbol{\beta}_0$ captures the expected post-leak price of a home with no benzene pollution. Notice this baseline effect is allowed to vary across the three experimental treatments. The coefficient $\boldsymbol{\beta}_1$ captures the additional decrease in price due to groundwater contamination. In the most flexible model $\boldsymbol{\beta}_1$ is a 12×1 vector, as shown in equation (3).

I estimate the effect of each of the four pollution levels on the price of home *h* in order to investigate how people believe prices respond to higher pollution levels, without making any parametric assumptions on the relationship. Comparing estimates of $\boldsymbol{\beta}_0$ and $\boldsymbol{\beta}_1$ across the three experimental treatments allows me to examine whether the presence of pollution affects home prices differently depending on whether there are potential health risks.

Coefficients $\boldsymbol{\beta}_2$ capture any differences in the post-leak price assessments based on respondents' prior familiarity and knowledge of the pollutant, its source, and

[59] The excluded category is 0 ppb. In more restrictive specifications I model pollution levels ppb_{hi} as a continuous scalar.

the exposure pathway. Finally, $\boldsymbol{\beta}_3$ allows me to control for any systematic differences in responses across different types of respondents and households.

IV. Data

IV.A. Data Collection

The questionnaire was self-administered by a convenience sample (n=303) at two University of Maryland events held in April and October 2010.[60] These were family events open to the public and meant for people of all ages. The main objective of these events was to get people familiar with the University and its research. Neither event was in any way related to housing, housing values, or environmental issues, such as LUSTs and groundwater pollution.

The first event was "Maryland Day" an annual university-wide affair held at the University of Maryland's main campus College Park (Prince George's County). Prior to the actual data collection, I was uncertain about how many responses I would be able to obtain. Therefore, at this event only the first two survey treatments, (i) *Public Water* and (ii) *Private Well*, were randomly assigned to participants. The second event is an annual open house sponsored by the College of Agriculture and Natural Resources at a research facility in Howard County (just north of and adjacent to Prince George's County). Again, due to uncertainty as to how many responses could be collected, only the third treatment, (iii) *Well with Filter*, was assigned to participants at the second event.

[60] One respondent was eliminated from the analysis because the responses were unrealistic and orders of magnitude larger than the rest of the sample.

At both events I had a booth where event attendees were invited to take the pen-and-paper questionnaire.[61] People were not told the specific topic of the questionnaire ahead of time. They were simply asked if they would like to participate in a research project, and that they would be asked questions about their home and neighborhood. As an additional incentive, I offered raffle tickets for the chance to win an iPod Shuffle. It took respondents about 10 minutes on average to complete the questionnaire.

IV.B. Experimental Treatments and Price Responses

Out of the 303 participants, 98 were randomly assigned to the *Well Water* scenario, 99 to *Public Water*, and 106 to the *Well with Filter* scenario. As discussed in section III.C, the dependent variable in the econometric models is the post-leak sale price (p_{hi}^{1}). I am interested in how people believe home prices are affected by different levels of pollution, and how this effect may differ across the three exposure pathway scenarios. Each of the 303 respondents were asked to assess the sale price of three homes with varying levels of pollution, yielding n=909 observations. Individuals did not always respond to the valuation questions: there were 89 missing values (9.79%).

The distribution of the remaining 820 home price responses is displayed in figure 3. This is a fairly wide distribution, ranging from $0 to $600,000. The majority of responses (n=628 or 76.6% of the valid responses) indicated that prices would be lower after the leak and subsequent groundwater contamination. The post-pollution prices were believed to remain at the average pre-leak price of $400,000 in 172

[61] To ensure a random and independent sample, interviewers were instructed to intercept every third person, and to not allow multiple individuals from the same group to take the questionnaire.

instances. In n=20 cases (2.4%) participants actually indicated an increase in price after the discovery of a LUST. In all these cases the homes were specified as having no groundwater pollution and/or an exposure pathway was not present (i.e., the assigned scenario was *Public Water* or *Well with Filter*). Such responses seem reasonable; respondents likely rationalized that uncontaminated homes are relatively more valuable when surrounded by contaminated homes. On average respondents believe the home price after the leak is only $293,903, a 26.5% depreciation from the average pre-leak price of $400,000.

The distribution of the price responses by experimental treatments are shown in figure 4. In the *Well Water* scenario there is a lower density of price responses around the average pre-leak price of $400,000, and a higher density among the lowest sale prices, relative to the other two experimental treatments. This suggests that when an exposure pathway is present, and the residents of the home face potential health risks, respondents do believe prices capitalize this additional risk premium.

The mean price responses across the experimental treatments are shown in table 3. First looking at all homes, as expected we see that prices are lower when an exposure path is present (as specified in the *Well Water* scenario).[62] Home prices are slightly higher, on average, in the *Well with Filter* scenario compared to *Public Water*, but this is not a statistically significant difference. Thus it appears responses are similar in the two situations where pollution is present but there are no health risks.

[62] Univariate t-tests comparing mean price response of the *Well Water* scenario to *Public Water* and *Well with Filter* yield t = 2.410 (p=0.0163) and t=3.622 (p=0.0003), respectively.

Pollution levels at homes B and C are randomly assigned, but home A is always specified as having 0 ppb benzene in the groundwater. The mean post-leak price of home A across the entire sample is $311,411, suggesting that respondents believe home prices will decline by 22.1% just because a LUST is in the neighborhood. Comparing the mean price responses for home A across the treatments, in table 3 we still see that prices decline most in the *Well Water* scenario, but this difference is not statistically significant. In section V, I conduct a more rigorous econometric analysis controlling for the experimental treatments and assigned contamination levels simultaneously.

IV.C. Descriptive Statistics

Table 4 displays descriptive statistics regarding the survey respondents' homes and neighborhoods. About 93.4% of respondents are Maryland residents. Most live in single family homes (71.3%), are homeowners (93.4%), and classify their neighborhood as suburban (75.3%). Only 17.5% of the sample currently lives in a home that relies on a private groundwater well, but 41.2% have at some point lived in a home with a well (as seen in table 5).

In table 5 I present variables denoting the respondents' prior knowledge and experience with water contamination and LUSTs. Only about 8.0% of the respondents report having water quality issues at their current home, but most (81.5%) are familiar with the term "parts-per-billion," which is the units in which the concentration of a pollutant in groundwater is often reported. Slightly less than half of the sample (45.9%) has heard of benzene contamination in water, and 79.0% have previously heard of leaking underground storage tanks before. Only 9.3% of participants report having a LUST in their neighborhood.

Summary statistics of the individual respondents and their households are shown in table 6. The average respondent is 44 years old and has 1.2 children. About 75.3% of the sample has obtained a bachelor's or higher level degree. The majority of respondents have no affiliation with the University of Maryland (i.e., they are not students, employees, or alumni).

This is a convenience sample consisting mainly of Maryland residents (93%), and my main objective is to analyze within sample variation in response to the experimentally assigned scenarios. Nonetheless, in table 7 I provide a brief comparison to the broader population of Maryland. A higher proportion of people in the sample has at least a Bachelor's degree, and reports a higher household income relative to the rest of the state. Neither is surprising since the sample was drawn from attendees at University events, and the respondents are from relatively affluent counties.[63] A higher percentage of households in my sample are homeowners and have children under 18. The age composition of my sample, relative to the state, is similar for some age groups, but my sample is more concentrated with respondents that are 45 to 54 years old, and contains a smaller percentage of respondents over 65.

[63] Out of the 303 participants that provided their county of residence 28% were from Howard, 26% from Prince George's, 14% from Montgomery, 6% from Baltimore, and 6% from Anne Arundel. With the exception of Baltimore County, these counties all report median household income levels higher than the State median. The remainder of the respondents were from other Maryland Counties (n=33), out of state (n=20), or did not report their county of residence (n=10).

IV.D. Comparison of Sample across Venues

About 36% of respondents from the first event are residents of Prince George's County, compared to only 7% at the second event. As one may expect, most of the participants at the second event (64%) are from Howard County compared to only 8% at the first event.

The first two experimental treatments (*Public Water* and *Private Well*) were randomly assigned to respondents only at the first event, but the third treatment (*Well with Filter*) was assigned to respondents only at the second event. In order to have a clean comparison the sample of respondents from these two events must be comparable. In tables 8 through 10 I present several univariate t-tests comparing the mean values of respondent characteristics across these two samples. The means of the two samples are statistically different (at the 5% level) for only seven out of 26 variables. The majority of participants in both samples live in suburban areas, but the second event sample has a higher proportion of people living in rural areas (22.6% v. 11.2%). Rural areas are less likely to be connected to the public water system, and indeed, a higher proportion of the second event sample consists of people who have lived in a home served by a private well. Respondents are similar in terms of knowledge and experience with water contamination and LUSTs. On average, the respondents are also similar in education, age, and number of children.

Overall, I believe respondents across these two samples are similar, and do not suspect that any differences will influence their valuations in response to the experimental treatments. For good measure I control for the individual characteristics of respondents in my regression models.

V. Results

V.A. Main Results

The base regressions are presented in table 11. In model A, I estimate a version of equation (2) where price is simply a linear function of the concentration of benzene pollution in the groundwater beneath the home. The intercept estimate of $309,150 implies that on average respondents believe that the mere presence of a LUST will lead to a $90,850 decrease in property values, a 22.7% depreciation (relative to the average pre-leak price of $400,000). The coefficient estimate on *pollution* suggests that a 1 ppb increase in benzene contamination leads to an additional $5,767 decrease in price.

There is no particular reason to assume that the effect of contamination on price is linear. Respondents were told that the regulatory standard of 5 ppb was set "to protect human health with a wide margin of safety." Individuals may perceive contamination levels above this standard as more hazardous (Smith et al., 1990; Johnson and Chess, 2003; Johnson, 2008). Therefore, I expect an asymmetric effect of pollution on home prices, where prices decline at a faster rate as pollution levels exceed the standard.

In model B I estimate a piece-wise linear relationship, allowing for a kink at the 5 ppb standard. When pollution levels are below the standard there is a small and statistically insignificant decrease in price for each additional part-per-billion of benzene. However, once the standard is exceeded we see a $5,931 (=2,402+3,529) decrease in price for each additional parts-per-billion, a statistically significant 1.48% depreciation, relative to the average pre-leak price of $400,000.[64]

Figure 5 clearly shows a more pronounced decline in price at pollution levels above the standard (5 ppb), suggesting that respondents used this regulatory standard as a reference point in forming their risk perceptions, and in turn, how home values would be affected. For good measure I estimate a more flexible form in model C by including a dummy variable for each of the contamination levels. At levels below the standard, the effect of pollution on price is negative, but relatively small and statistically insignificant, as seen by the coefficient estimates for *1 ppb* and *4 ppb*. However, the coefficients on *6 ppb* and *9 ppb* show that these levels of pollution result in decreases of $37,743 (9.44%) and $52,945 (13.24%), respectively. Comparing the coefficients on *4 ppb* and *6 ppb* shows that people view departures from the 5 ppb standard asymmetrically.

In model D a separate intercept is included for each of the three exposure pathway scenarios. In other words, the effect of the LUST on prices is allowed to vary depending on whether the hypothetical homes are on the public water system, rely on private wells, or rely on wells but have filters installed. Notice the increase in the adjusted R-square (0.032 to 0.884), implying that controlling for the scenarios helps explain how participants believe that prices respond to pollution. As expected, a LUST decreases prices most at homes relying on private wells, which is where the households are truly at risk. The *private well* coefficient suggests a $111,319 decrease in price relative to the initial $400,000 average pre-leak home value, a 27.8% decline.

[64] F-tests for joint significance of the pollution (ppb) variable and its interaction with the dummy denoting when the standard is exceeded yield an F-stat=13.30, thus I reject the null that the associated coefficients are jointly equal to zero.

In contrast, among homes on the public water system and where a filter was installed there is a smaller decline in price, $88,683 (22.1%) and $77,004 (19.3%), respectively.[65]

Nevertheless, this is still a fairly sizable discount in home values considering that there is no exposure to the benzene contamination, and therefore no health risks (at least not via the drinking water). The respondents may believe house prices decline by this much because of uncertainties in future risks or potential health risks through other means of exposure.[66]

In model E I examine how reported prices respond to the disamenity even if the groundwater beneath the home itself is not contaminated. I focus only on home A, which was always assigned 0 ppb contamination. The largest decrease in price is still among homes on private wells, but this is not statistically different from the other two experimental scenarios. Therefore, the assigned survey scenarios do not seem to matter when there is no contamination present, but respondents still believe there is a statistically significant 19.57% to 24.95% depreciation because these homes are merely near a LUST site.

Recall that participants were told that prior to the leak, homes in this neighborhood are worth $400,000, on average. It is possible that respondents may infer differences in the pre-leak prices based on the aerial photo (figures 1 and 2), as

[65] F-tests show that the larger decrease in price in the *well water* scenario is statistically different from the *public water* and *well with filter* scenarios (f-stat=6.00 and 13.61, respectively). There is no statistical difference between the *public water* and *well with filter* scenarios.

[66] For example, although it was not discussed in the survey, respondents may be aware of vapor intrusion, which is when pollutants evaporate into harmful vapors and migrate through the soil into basements and homes This poses short-term risks such as headaches, nausea, dizziness, and possible explosions (Toccalino, 2005; Béraud, 1997; and MDE, http://www.mde.state.md.us/assets/document/LRP%20Vapor%20Intrusion%20Guidance(6).pdf, accessed March 19,2011).

shown by equation 2). To account for this possibility, in table 12 I re-estimate models A through D, but I now include fixed effects for each home. Models F through I show that the previous results are robust to the inclusion of these home fixed effects. Across all four models, I fail to reject the null hypothesis that the home specific intercepts are statistically equivalent.

In models J, K, and L in table 13, I compare whether prices are affected differently across the three survey scenarios by higher levels of contamination. Model F includes separate intercepts for each of the three scenarios, and interaction terms with each of the contamination level dummies. This allows the effect of contamination on price to vary across all pollution levels and the three experimental scenarios. Respondent characteristics are added in model G, including education, children, income, and age (which I discuss in subsection V.B). Additional characteristics are added in model L, namely whether the respondent is a student, university employee, alumnus, etc. (which are found to be statistically insignificant, both individually and jointly).[67]

In table 13, the results across the three exposure pathway scenarios are robust across all three specifications. The intercept terms are below the initial pre-leak price of $400,000, suggesting people believe prices decline even if there is no groundwater pollution at the home itself. Based on the most complete specification, model H, this depreciation ranges from 18.66% to 20.97%, with the largest depreciation in the *Private Well* scenario. The scenario specific intercepts, however, are not statistically different from each other. Beyond this initial depreciation, groundwater pollution levels below the regulatory standard have a statistically insignificant effect on price.

[67] The full regression results are presented in table A1 in Appendix A.

However, once the regulatory limit is exceeded, announced home prices decline with higher pollution levels, as can be seen by the coefficient estimates associated with the *6 ppb* and *9 ppb* variables. This decline is strongest among respondents who were randomly assigned to the *Private Well* Scenario. For example, in model H, the price of a home that is simply near the LUST site will decline by 20.97% (relative to the average pre-leak price of $400,000). If the groundwater well at this home is found to have 6 ppb of benzene then the home is worth 32.61% less, and at 9 ppb a 41.33% depreciation is reported.

Statistical tests fail to reject the null that the effects of higher pollution levels on home values are different across the *Private Well* and *Public Water* scenarios.[68] Why might this be? Even though respondents were reminded that an exposure pathway is only present in the *Private Well* scenario, perhaps they remained concerned with other potential exposure pathways, future uncertainties, or simply did not keep this lack of exposure pathway in mind when answering the valuation questions, and thus thought that property values would decline in a similar fashion. It could also be that the decline in price was motivated by non-health concerns about environmental quality, public stigma towards the homes (Messer et al, 2006; Gregory and Scatterfield, 2002), or belief that others would misunderstand the lack of health risks.

Respondents may better comprehend that a filter reduces health risks. In fact, the *Well with Filter* scenario clearly specifies that all contamination is removed, and thus all health risks eliminated (see section III.A and figure 2). As seen in table 13 by

[68] Wald tests comparing the coefficients on *1 ppb*, *4 ppb*, *6 ppb*, and *9 ppb* across the *Private Well* and *Public Water* treatments, and just *6 ppb*, and *9 ppb*, yield f-stats of 0.36 and 0.17, respectively.

the coefficients on *6 ppb* and *9 ppb*, under the *Well with filter* scenario the additional decline in price at pollution levels above the standard is relatively weak. Focusing on model H, statistical tests reject the null hypothesis that the coefficients on each of the contamination levels are equal across the *Private Well* and *Well with Filter* scenarios (p=0.0527). This holds even when focusing on just benzene levels above the 5 ppb standard (p=0.0086), suggesting that the respondents do not believe prices decrease as much at higher contamination levels when a filter is installed. In fact, all the contamination level coefficients in the filter scenario are jointly insignificant. When a filter is installed people in this sample, on average, do not believe prices decline more at higher pollution levels. Of course the mere presence of the LUST still leads to a significant 18.66% depreciation.

V.B. Results with Individual Characteristics

Next I estimate several regressions to investigate whether respondents' socio-economic status and familiarity with the pollution source, exposure pathway, and the pollutant itself has any bearing on how they believe home values are affected by groundwater pollution.

The regressions in table 14 build off of model K (in table 13).[69] Only the socio-demographic characteristics and variables describing experience with the pollutant and exposure pathway are presented in table 14.[70] I find that a participant's age and income have no systematic effect on announced home prices. Education,

[69] To avoid collinearity issues I work off of model K instead of model L (which included variables denoting whether the respondent was an undergraduate student, graduate, alumnus, or University employee). The coefficient estimates for these excluded variables were both jointly and individually insignificant.
[70] The full regression results are presented in table A2 in Appendix A.

however, matters: the post-leak prices reported by respondents who have at least a bachelor's degree are not as low as those reported by others, all else constant. Respondents who have a child less than 5 years old also report higher post-leak home prices. This is contrary to my initial expectations. I initially expected that individuals with young children may be more concerned about the health risks to households. Of course the valuation exercise asked the respondents for their third party assessment of the sale price, and so in this hypothetical exercise their household itself would not be affected. The sign and statistical significance of these results is robust across the remaining specifications in table 14.

In model M, the dummy variable *Well Water* is added, which denotes that the respondent currently or previously lived in a home that relied on a private groundwater well. This is meant to proxy familiarity with the primary exposure pathway. In earlier focus groups we found that people who have always lived in homes connected to the public water system sometimes had difficulties making the distinction between their tap water and the groundwater beneath their homes (Alberini and Guignet, 2010). The results here, however, suggest that prior experience with the private wells (the primary exposure pathway) has no significant effect on announced post-leak prices.

To investigate whether a respondent's familiarity with the contaminant and the unit of measurement have any bearing on announced post-leak prices, model N includes the dummy variables *benzene* and *parts-per-billion*. In general, people tend to over-perceive small risks, such as environmental health risks; however, people who are relatively familiar with these risks may not over-perceive them as much (Viscusi, 1998). Both coefficient estimates are positive. This provides some weak evidence that respondents who are familiar with benzene and how pollution levels are measured do not perceive a LUST to be as much of a threat, and therefore do not believe prices will decline as much. However, the coefficient on *parts-per-billion* is only marginally significant, and a respondent's familiarity with benzene seems to have no significant affect on announced post-leak prices.

Model O includes indicator variables denoting that the respondent is familiar with leaking underground storage tanks (*LUSTs*), and is aware of a LUST site in their neighborhood. The former has a relatively small and insignificant effect on price responses, but the 28 individuals who report having a LUST in their neighborhood (n=84 observations) believe home values will decline an additional $45,550 (11.39%), all else constant. Model P includes the dummy variable *recent_in_market*, which equals one for the 104 participants (n=312 observations) who bought, sold, or have been actively looking for a home within the last 5 years. The small and statistically insignificant coefficient suggests that familiarity and recent activity in the housing market has little effect on reported post-leak home prices.

VI. Conclusion

To environmental economists, hedonic property value methods are an attractive non-market valuation technique because welfare estimates are inferred from actual behavior, and, at least in theory, all aspects of a welfare change are capitalized in prices. However, in conducting hedonic studies researchers are often forced to make untested assumptions regarding the public's awareness and perceptions of the environmental disamenity of interest, and how they measure this disamenity. Stated preference methods, on the other hand, provide an opportunity to examine how home values might be affected when we *know* exactly what is being valued, and do not have to make restrictive assumptions.

The goal of this stated preference study is to express an environmental good in terms of pollution levels, and investigate how people value environmental quality and health risks by measuring the impacts on home prices. I incorporate an experimental design to analyze how reported home prices are affected by the discovery of a leaking underground storage tank (LUST), the presence of an exposure pathway, the level of groundwater pollution (parts-per-billion of benzene), and when pollution levels exceed the regulatory standard. Respondents use this information to form their own perceptions of environmental and health risks, and in turn, assess how home values are affected.[71]

Corresponding to the hedonic analysis in chapter 2, the information I provide to respondents is the same that the Maryland Department of Environment (MDE) provides to households in Maryland whose groundwater wells are tested for pollution from a LUST site. The questionnaire was self-administered by a convenience sample of Maryland residents in April and October, 2010. My interests are not in the magnitude of the estimated price declines from pollution, but rather the overall message and within sample comparisons of the experimental treatments.

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[71] In Chapter 4 of this dissertation I present a separate stated preference study where we experiment with a second approach; respondents are explicitly presented with objective health risks. A third approach, which is the one taken in past stated preference studies (e.g., Jenkins-Smith et al., 2002; Chattopadhyay et al., 2005; Simons and Winson-Geideman, 2005), is to convey the environmental good qualitatively by describing some scenario.

I find an 18% to 24% depreciation in announced post-leak home prices even if the groundwater at the home itself is not contaminated. The largest decline is found when the exposure pathway (i.e., a private groundwater well) is present. However, when the groundwater at the home itself is not contaminated, this effect is not statistically different from the other two experimental treatments, where a clear exposure pathway is not present.

As expected, home prices decrease further at higher levels of groundwater pollution beneath the home, an effect that is more pronounced once the regulatory standard is exceeded. Respondents likely interpret pollution standards as a ceiling of what is considered "safe" (Smith et al., 1990; Johnson and Chess, 2003; Johnson, 2008). I find evidence that the effect of groundwater pollution on announced home prices is strongest when the homes use private wells, and thus when there is an increase in health risks. If a filter is installed at the home and the respondents are explicitly told that it eliminates all health risks, then higher pollution levels have a small and statistically insignificant effect on reported prices, but the mere presence of a LUST still leads to an initial 18% price depreciation.

So, are stated preference techniques a viable alternative to hedonic property value models? The results from this study suggest that people *are* capable of interpreting pollution concentrations, and in turn, expressing how they think property values are impacted. The reported home prices capitalize the presence of pollution in ways that are consistent with economic theory, and are comparable to previous studies of how house prices are affected by LUSTs and groundwater pollution.

In a hedonic study of actual home sales in Maine, Boyle et al. (2010) find that an increase in arsenic pollution from 0.05 mg/L to 0.06 mg/L (a 20% increase above the standard) decreases home prices by 0.5-1.0%. In this stated preference study I find that an increase in benzene pollution from 5 ppb to 6 ppb (a 20% increase above the standard) leads to a 1.48% decline in reported home prices.

In chapter 2 of this dissertation, I presented a parallel hedonic property value study of single-family home sales in Maryland. There I find a 9-12% depreciation among homes where the private well was tested for petroleum contamination from a LUST. These households were subsequently informed of the regulatory standards and the contamination levels in their well. In this stated preference study, where respondents are given analogous information, the percent decrease in reported home prices is twice as much (18-24%). This is slightly below, but comparable to, the 25-33% decline in home prices that Simons and Winson-Geideman (2005) found in their stated preference study on LUSTs.

Simons and Winson-Geideman (2005) explicitly put respondents in the role of the buyer or seller of a home. We attempted this approach in earlier focus groups, but found that participants often took a firm moral stance, deeming a property unsellable, or stating they would not purchase the property for any price, even if the home itself was not contaminated (Alberini and Guignet, 2010). Based on this evidence, in the study presented in this dissertation chapter I asked respondents to assess changes in home values from the perspective of an outside third-party (i.e., not as the buyer or seller).

Psychologists and sociologists have found that this third-party or indirect valuation approach may reduce hypothetical biases that arise when respondents are asked questions about emotionally or socially sensitive topics, such as environmental pollution and health risks (Kahneman and Tversky, 1979; Fisher, 1983; Epley and Dunning, 2000). Only a few studies have examined the potential of this approach in minimizing hypothetical biases in non-market valuation (Lusk and Norwood, 2009a, 2009b; Yadav et al., 2010), and no one to my knowledge has done so in the context of housing. It may be helpful in future stated preference research to compare reported home prices from this third-party perspective to those when respondents are placed in the role of a homebuyer and seller, and also to comparable hedonic property value studies.

Figures and Tables

Figure 1. Aerial Photo of Leak and Groundwater Pollution.

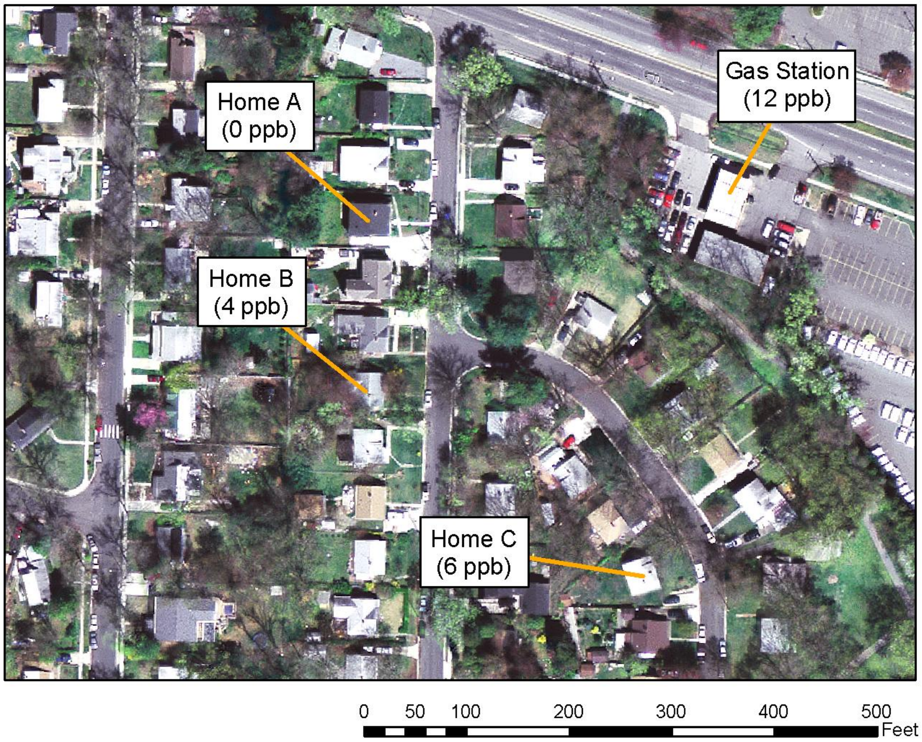


Figure 2. Aerial Photo for Scenario 3: *Well with Filter.*

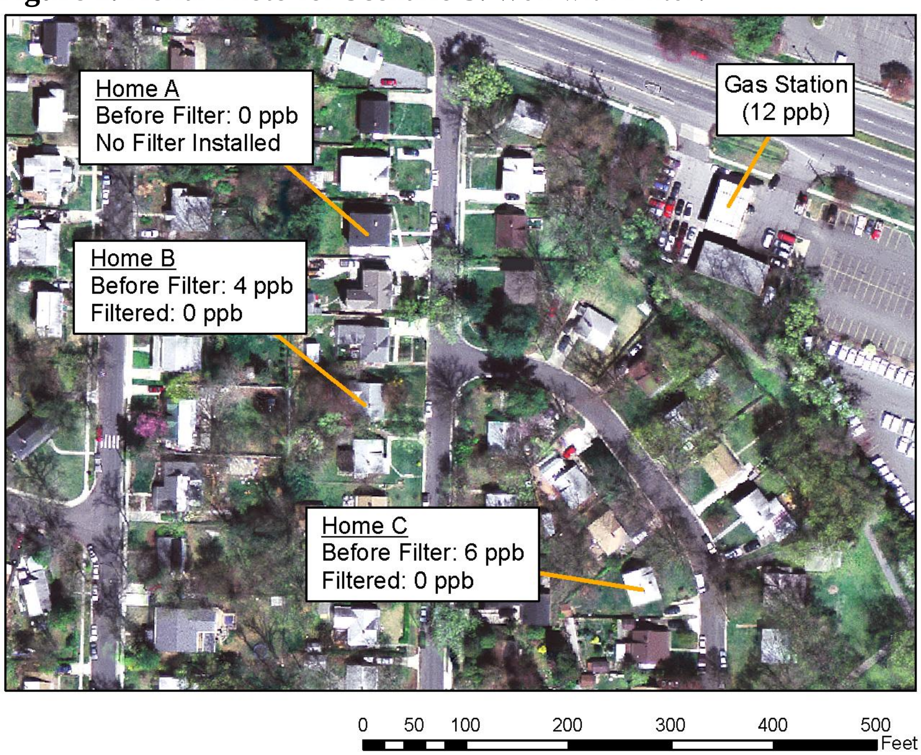


Figure 3. Kernel Density Estimate of Post-pollution Price Responses.

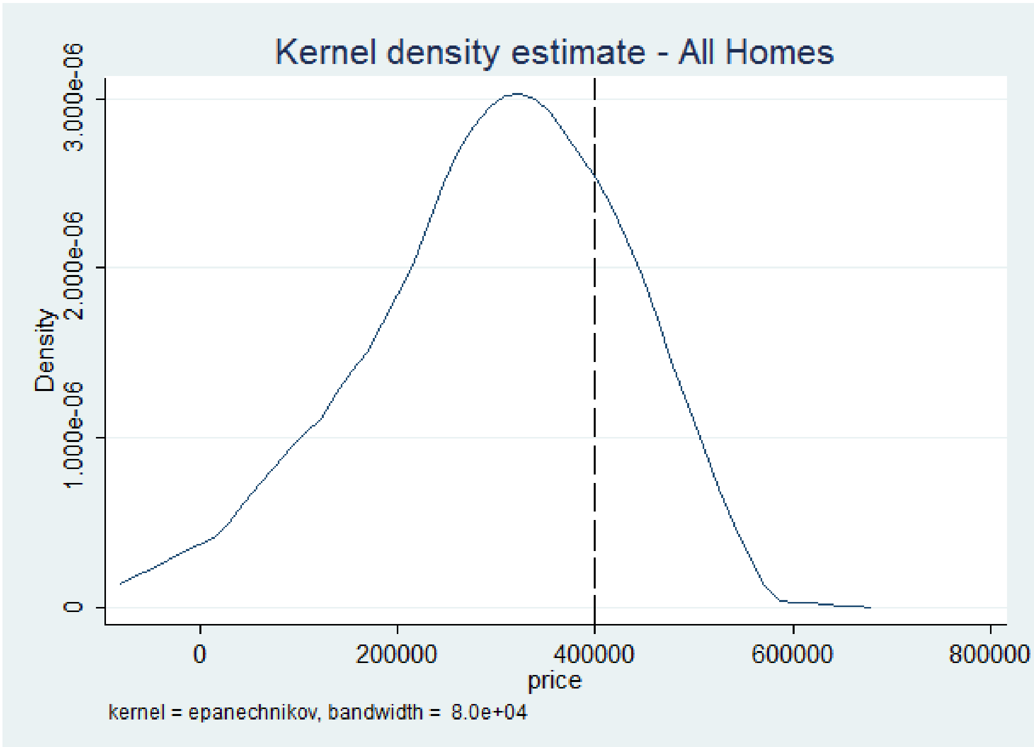


Figure 4. Kernel Density of Post-pollution Price Responses across Scenarios.

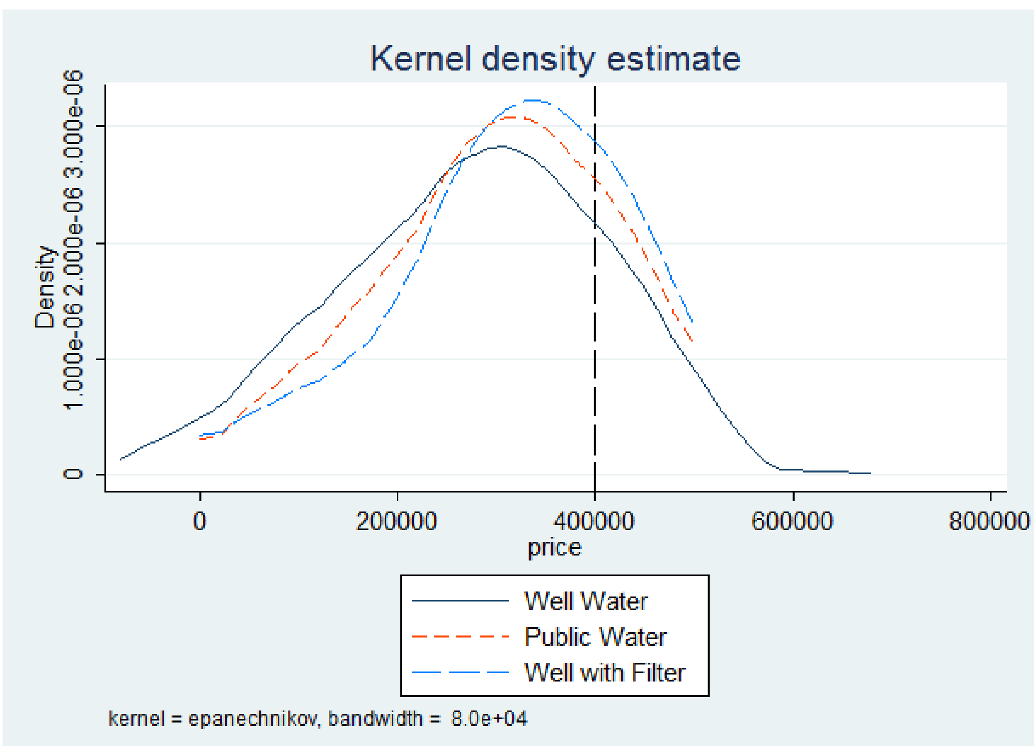
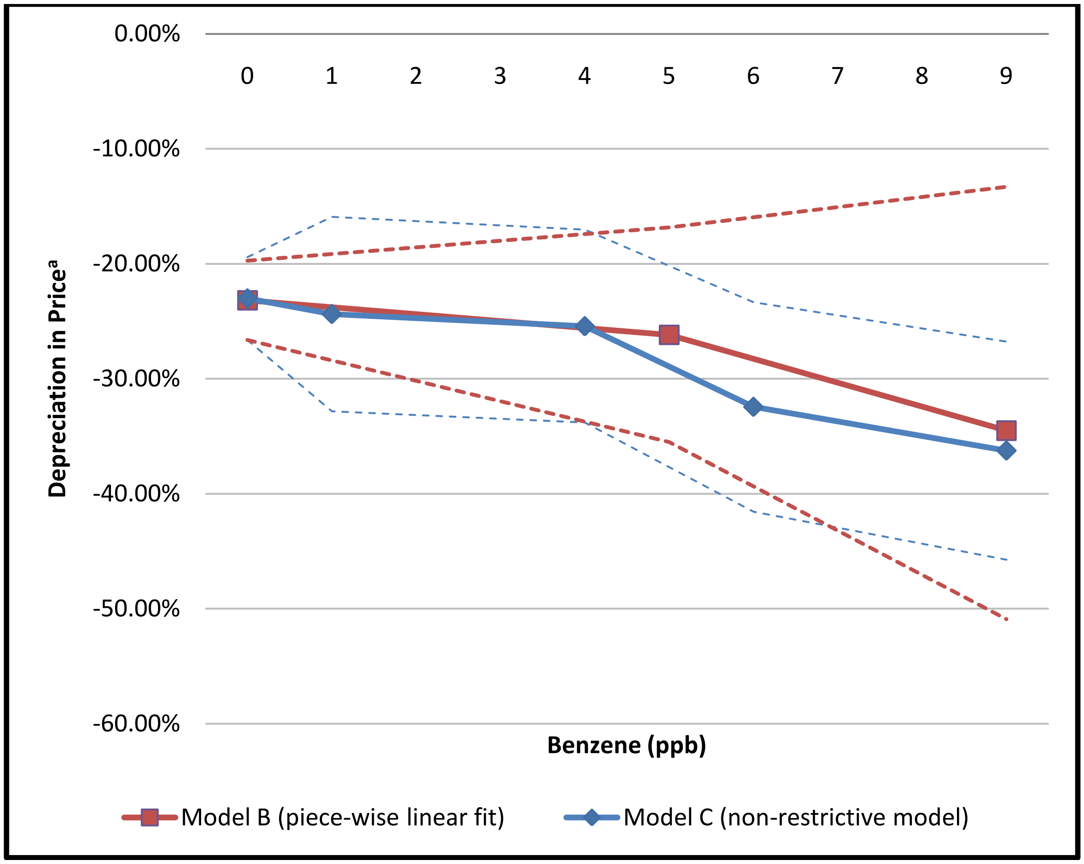


Figure 5. Price Trends at Higher Benzene Contamination Levels.



Note: Dashed lines denote 95% confidence interval.
a. Percent depreciation is relative to the average pre-leak home price of $400,000.

Table 1. Experimental Survey Treatments: The Exposure Pathway Scenarios.

Scenario 1: Private Well

In this neighborhood the homes are worth $400,000 on average, and rely on private groundwater wells.

Now suppose a leak occurs at one of the tanks at the gas station in the neighborhood. The leak has been stopped, but no cleanup has been undertaken. The groundwater around the site is tested for benzene and the test results for three of the homes are shown in the photo below.

Scenario 2: Public Water

In this neighborhood the homes are worth $400,000 on average, and served by the public water system, which gets its water from a distant reservoir.

Now suppose a leak occurs at one of the tanks at the gas station in the neighborhood. The leak has been stopped, but no cleanup has been undertaken. The groundwater around the site is tested for benzene and the test results for three of the homes are shown in the photo below.

Scenario 3: Well with Filter

<*Treatment 1: Private Well* text>

If any contamination is found in the groundwater beneath a home then a water filter is installed so that the water at the home is safe for drinking, cooking, bathing, and so forth. This is done at no cost to the homeowner.

Table 2. Summary of Study Design.

	# of Variants	Levels/Variants
Pollution Levels:		
Home A	1	0 ppb
Home B	5	0, 1, 4, 6, 9 ppb
Home C	5	0, 1, 4, 6, 9 ppb
Exposure Pathway Scenario:	3	1) *Private Well*
		2) *Public Water*
		3) *Well with filter*

Table 3. Mean Price Responses across Experimental Treatments.

Treatment:	**All Homes Mean***	**Just Home A (0 ppb) Mean***	**Just Homes B & C† Mean***
Well Water	$ 274,717	$ 300,187	$ 261,840
	(113,895)	(118,546)	(109,564)
Public Water	$ 297,567	$ 321,719	$ 285,213
	(105,108)	(106,732)	(102,387)
Well with Filter	$ 308,713	$ 312,495	$ 306,802
	(107,277)	(110,389)	(105,915)

*Std Deviation in parentheses.
† Homes B and C randomly assigned a pollution level of 0, 1, 4, 6, or 9 ppb.

Table 4. Descriptive Statistics of Respondents' Home and Neighborhood.

Variable*	Obs	Mean	Std. Dev.
Homeowner - Owns Home	303	0.8086	0.3941
LiveMD - Lives in Maryland	303	0.9340	0.2487
Single - Lives in Single Family Home	303	0.7129	0.4532
Rural - Live in rural neighborhood	303	0.1518	0.3594
Suburb - Lives in suburban neighborhood	303	0.7525	0.4323
Urban - Lives in Urban Area	303	0.0957	0.2947
Pvt_Water - Current home uses private well	303	0.1749	0.3805
Pub_Water - Current home connected to public water system	303	0.7723	0.4201

*Note: All variables are binary indicator variables unless otherwise noted.

Table 5. Descriptive Statistics on Respondents' Prior Knowledge and Experience.

Variable*	Obs	Mean	Std. Dev.
Well Water - has lived in home that used private well	303	0.4191	0.4942
Water_Issue - Has had water quality issue at home	303	0.0792	0.2705
Parts-per-billion - heard of the term "parts-per-billion" before	303	0.8152	0.3888
Benzene - heard of benzene in drinking water	292	0.4589	0.4992
LUSTs - heard of "leaking underground storage tanks" before	300	0.7900	0.4080
LUST in Neighborhood - Aware of LUST in own neighborhood	300	0.0933	0.2914

*Note: All variables are binary indicator variables unless otherwise noted.

Table 6. Descriptive Statistics on Respondent and Household Attributes.

Variable	Obs	Mean	Std. Dev.	Min	Max
Age - age of respondent (years)	290	44.3138	12.6915	18	80
Kids - Has child(ren) under 18	303	0.6568	0.4756	0	1
Kids5 - Has child(ren) under 5	303	0.1749	0.3805	0	1
Children - # of Children under 18	293	1.2253	1.1274	0	5
Children5 - # of Children under 5	293	0.1741	0.4462	0	2
Education - Level of education (1 to 6 scale)[b]	303	4.9241	1.4909	0	6
Bachelor's - completed a bachelor's or higher degree	303	0.7525	0.4323	0	1
Undergrad - respondent is undergraduate student	303	0.0660	0.2487	0	1
Grad - respondent is graduate student	303	0.0627	0.2428	0	1
Alumni - respondent is Univ. of Maryland alumni	303	0.2112	0.4089	0	1
Employee - respondent employee of the Univ. of Maryland	303	0.1551	0.3626	0	1
Income - Annual household income (1 to 9 scale)[c]	278	5.6223	2.0546	1	9

a. All variables are binary indicator variables unless otherwise noted.
b. 1= some high school, 2=high school diploma, 3=some college, 4=associate degree, 5=bachelor's degree, 6= post graduate education
c. 1=less than $35,000; 2=$35,000-44,999; 3=$45,000-54,999; 4=$55,000-74,999; 5=$75,000-99,999; 6=$100,000-149,999; 7=$150,000-199,999; 8=$200,000-250,000;

9=more than $250,000

Table 7. Comparison of Convenience Sample to Maryland 2000 Census Data.

	Study Sample	State of Maryland
Bachelor's Degree or higher	75.25%	31.45%
Children under 18 years	65.68%	37.31%
Own home	80.86%	67.74%
Median household income (2010$)	$125,000	$69,197
Age		
18 to 19 years	3.79%	3.47%
20 to 24 years	7.24%	7.97%
25 to 34 years	10.34%	19.00%
35 to 44 years	24.48%	23.25%
45 to 54 years	34.48%	19.16%
55 to 64 years	13.79%	11.94%
65+ years	5.86%	15.21%

Table 8. Comparison of Characteristics across Event Samples: Home and Neighborhood Attributes.

	Event 1			Event 2			
Variable	Obs	Mean	Std Dev	Obs	Mean	Std Dev	t-stat
Homeowner	197	0.7919	0.407	106	0.8396	0.3687	1.04
LiveMD	197	0.9086	0.2889	106	0.9811	0.1367	2.96***
Single	197	0.6904	0.4635	106	0.7547	0.4323	1.21
Rural	197	0.1117	0.3158	106	0.2264	0.4205	2.46**
Suburb	197	0.7716	0.4209	106	0.717	0.4526	-1.03
Urban	197	0.1168	0.3219	106	0.0566	0.2322	-1.87*
Pvt_Water	197	0.132	0.3393	106	0.2547	0.4378	2.51**
Pub_Water	197	0.8173	0.3874	106	0.6887	0.4652	-2.43**

Table 9. Comparison of Characteristics across Event Samples: Prior Experience with LUSTs, Pollution, and Groundwater.

	Event 1			Event 2			
Variable	Obs	Mean	Std Dev	Obs	Mean	Std Dev	t-stat
Well Water	197	0.3553	0.4798	106	0.5377	0.5009	3.07***
Water_Issue	197	0.0792	0.2659	106	0.0849	0.2801	0.26
Parts-per-billion	197	0.8071	0.3956	106	0.8302	0.3773	0.50
Benzene	190	0.4632	0.5	102	0.451	0.5	-0.02
LUSTs	194	0.7629	0.4264	106	0.8396	0.3687	1.63
LUST in Neighborhood	194	0.1082	0.3115	106	0.066	0.2495	-1.28

Table 10. Comparison of Characteristics across Event Samples: Respondent and Household Attributes.

	Event 1			Event 2			
Variable	Obs	Mean	Std Dev	Obs	Mean	Std Dev	t-stat
Age	187	43.72	12.93	103	45.39	12.23	1.09
Kids	197	0.6497	0.4783	106	0.6698	0.4725	0.35
Kids5	197	0.1421	0.3501	106	0.2358	0.4265	1.94*
Children	190	1.1894	1.123	103	1.2913	1.1257	0.74
Children5	190	0.1421	0.4313	103	0.233	0.4687	1.63
Education	197	4.88	1.55	106	5.01	1.37	0.76
Bachelors	197	0.761	0.4446	106	0.7925	0.4075	1.21
Undergrad	197	0.0812	0.2739	106	0.0377	0.1915	-1.61
Grad	197	0.0812	0.2739	106	0.0283	0.1666	-2.09**
Alumni	197	0.2386	0.4273	106	0.1604	0.3687	-1.66*
Employee	197	0.1726	0.3789	106	0.1226	0.3296	-1.19
Income	183	5.44	2.18	95	5.98	1.74	2.25**

Table 11. Basic Regression Results (dependent variable = $price_{hi}$)

VARIABLES[a]	(A)	(B)	(C)	(D)	(E)[b]
Pollution (ppb)	-5,767***	-2,402			
	(1,128)	(2,391)			
× above 5 ppb		-3,529			
		(2,417)			
1 ppb			-5,431	-4,632	
			(9,893)	(10,983)	
4 ppb			-9,652	-9,791	
			(9,731)	(11,102)	
6 ppb			-37,743***	-38,953***	
			(11,176)	(11,451)	
9 ppb			-52,945***	-52,231***	
			(11,948)	(11,926)	
Public Water				311,317***	321,719***
				(7,756)	(11,311)
Private Well				288,681***	300,187***
				(8,196)	(12,426)
Well with Filter				322,996***	312,495***
				(7,419)	(11,269)
Constant	309,150***	307,290***	307,922***		
	(6,902)	(7,015)	(7,310)		
Observations	820	820	820	820	276
R-squared	0.030	0.032	0.032	0.884	0.887

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
a. All variables are binary indicator variables unless otherwise noted.
b. Only home A included in estimation.

Table 12. Basic Regression Results with Home Fixed Effects (dep variable = $price_{hi}$)

VARIABLES[a]	(F)	(G)	(H)	(I)
Pollution (ppb)	-5,360***	-513		
	(1,430)	(3,103)		
× above 5 ppb		-4,608*		
		(2,674)		
1 ppb			3,037	3,850
			(13,908)	(13,741)
4 ppb			-1,125	-1,249
			(13,764)	(13,669)
6 ppb			-29,348*	-30,543**
			(15,105)	(14,919)
9 ppb			-44,597***	-43,868***
			(14,891)	(14,474)
Public Water				314,830***
				(10,230)
Private Well				326,483***
				(10,718)
Well with Filter				292,169***
				(11,521)
Home Fixed Effects				
Home A	311,411***	311,411***	311,411***	
	(6,750)	(6,755)	(6,763)	
Home B	307,849***	302,530***	301,071***	-10,361
	(8,708)	(9,351)	(11,848)	(9,500)
Home C	304,915***	299,299***	297,868***	-13,564
	(8,361)	(9,172)	(11,602)	(9,349)
Wald Tests:				
Home Fixed Effects are equal (p-value)	0.78	1.65	1.28	0.82
	(p=0.4582)	(p=0.1941)	(p=0.2801)	(p=0.3656)
Observations	820	820	820	820
R-squared	0.882	0.882	0.882	0.884

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
a. All variables are binary indicator variables unless otherwise noted.

Table 13. Regression Results Across Experimental Treatments (dep variable=$price_{hi}$).

VARIABLES	(J)	(K)	(L)
Public Water	312,286***	293,112***	325,285***
	(10,013)	(54,271)	(72,073)
× *1 ppb*	12,244	3,125	1,064
	(18,470)	(14,308)	(14,663)
× *4 ppb*	-5,727	-5,977	-7,001
	(16,641)	(16,740)	(16,865)
× *6 ppb*	-45,897**	-45,554***	-44,924**
	(18,181)	(16,997)	(17,599)
× *9 ppb*	-73,952***	-65,927***	-65,923***
	(20,895)	(17,542)	(17,977)
Private Well	294,367***	280,206***	316,103***
	(10,755)	(56,443)	(75,857)
× *1 ppb*	-17,746	-20,462	-24,955
	(21,101)	(19,081)	(18,531)
× *4 ppb*	-6,744	-16,483	-16,784
	(18,931)	(15,834)	(15,568)
× *6 ppb*	-43,913**	-44,896**	-46,536**
	(21,303)	(21,761)	(21,248)
× *9 ppb*	-78,512***	-83,278***	-81,427***
	(18,836)	(21,029)	(19,967)
Well with Filter	316,700***	292,234***	325,374***
	(9,064)	(56,240)	(73,452)
× *1 ppb*	-8,097	1,287	-716
	(16,863)	(15,741)	(15,709)
× *4 ppb*	-16,042	-21,367	-23,930
	(21,328)	(16,585)	(16,527)
× *6 ppb*	-28,212	-34,490**	-32,172**
	(19,951)	(17,510)	(16,310)
× *9 ppb*	-5,172	-2,144	-2,505
	(20,875)	(16,244)	(16,346)
Individual Characteristics:			
Socio-economic	No	Yes	Yes
Relationship to Univ.	No	No	Yes
Observations	820	820	820
R-squared	0.886	0.898	0.899

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Note: All variables are binary indicator variables unless otherwise noted.
Full results presented in table A1 in Appendix A.

Table 14. Effect of Individual Characteristics and Hazard Familiarity on Post-leak Home Price Responses.

VARIABLES[a]	(K)[b]	(M)	(N)	(O)	(P)
Bachelor's degree or higher	56,448***	55,744***	52,507***	48,586**	48,017**
	(18,961)	(18,943)	(18,582)	(19,139)	(19,182)
Education Missing	7,083	5,831	8,628	3,276	3,658
	(57,655)	(54,939)	(54,780)	(56,151)	(57,046)
Has Children	-6,945	-7,249	-5,264	-7,677	-8,689
	(15,869)	(15,853)	(15,861)	(15,949)	(15,867)
Has Children under 5 yrs	38,679***	37,599***	38,265***	38,568**	39,810**
	(14,480)	(14,425)	(14,605)	(15,234)	(15,437)
Income (1 to 6 scale)	4,542	5,166	4,197	4,306	4,419
	(3,298)	(3,299)	(3,279)	(3,292)	(3,288)
Income Missing	-39,724	-39,763	-42,409	-41,555	-41,613
	(35,495)	(35,786)	(35,277)	(36,139)	(36,223)
Age (years)	-1,731	-1,866	-1,865	-1,860	-1,467
	(2,709)	(2,695)	(2,650)	(2,613)	(2,628)
Age^2	15	18	16	15	10
	(31)	(31)	(30)	(30)	(30)
Age missing	-81,724	-79,838	-72,850	-80,245	-76,365
	(71,153)	(70,558)	(70,483)	(70,829)	(70,910)
Well Water		-14,987	-15,842	-13,807	-13,580
		(11,593)	(11,636)	(11,887)	(11,857)
Benzene			452	425	1,288
			(11,911)	(12,165)	(12,617)
Benzene Missing			18,851	25,886	23,596
			(33,392)	(35,551)	(35,444)
Parts-per-billion			39,187*	35,415*	33,637*
			(20,382)	(20,245)	(20,317)
LUSTs				6,626	6,404
				(15,223)	(15,199)
LUST in Neighborhood				-45,550**	-46,528**
				(21,041)	(21,304)
recent_in_mkt					-7,157
					(12,939)
Treatment × ppb (dummies)	Yes	Yes	Yes	Yes	Yes
Observations	820	820	820	817	817
R-squared	0.898	0.898	0.900	0.902	0.902

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

Note: Full regression results are presented in table A2 of appendix.

a. All variables are binary indicator variables unless otherwise noted.

b. Model G is re-presented here for comparison (full results in table A1 of appendix).

Appendix A. Full Regression Results.

Table A1. Full Regression Results Across Experimental Treatments (dep variable= $price_{hi}$).

VARIABLES[a]	(J)	(K)	(L)
Public Water	312,286***	293,112***	325,285***
	(10,013)	(54,271)	(72,073)
× *1 ppb*	12,244	3,125	1,064
	(18,470)	(14,308)	(14,663)
× *4 ppb*	-5,727	-5,977	-7,001
	(16,641)	(16,740)	(16,865)
× *6 ppb*	-45,897**	-45,554***	-44,924**
	(18,181)	(16,997)	(17,599)
× *9 ppb*	-73,952***	-65,927***	-65,923***
	(20,895)	(17,542)	(17,977)
Private Well	294,367***	280,206***	316,103***
	(10,755)	(56,443)	(75,857)
× *1 ppb*	-17,746	-20,462	-24,955
	(21,101)	(19,081)	(18,531)
× *4 ppb*	-6,744	-16,483	-16,784
	(18,931)	(15,834)	(15,568)
× *6 ppb*	-43,913**	-44,896**	-46,536**
	(21,303)	(21,761)	(21,248)
× *9 ppb*	-78,512***	-83,278***	-81,427***
	(18,836)	(21,029)	(19,967)
Well with Filter	316,700***	292,234***	325,374***
	(9,064)	(56,240)	(73,452)
× *1 ppb*	-8,097	1,287	-716
	(16,863)	(15,741)	(15,709)
× *4 ppb*	-16,042	-21,367	-23,930
	(21,328)	(16,585)	(16,527)
× *6 ppb*	-28,212	-34,490**	-32,172**
	(19,951)	(17,510)	(16,310)
× *9 ppb*	-5,172	-2,144	-2,505
	(20,875)	(16,244)	(16,346)

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Table A1. Full Regression Results Across Experimental Treatments (continued).

VARIABLES[a]	(J)	(K)	(L)
--- Continued from Previous Page ---			
Bachelor's degree or higher		56,448***	52,225**
		(18,961)	(20,457)
Education Missing		7,083	1,913
		(57,655)	(58,403)
Has Children		-6,945	-7,184
		(15,869)	(15,619)
Has Children under 5 yrs		38,679***	37,852**
		(14,480)	(14,790)
Income (1 to 6 scale)		4,542	4,421
		(3,298)	(3,349)
Income Missing		-39,724	-42,630
		(35,495)	(34,694)
Age (years)		-1,731	-2,747
		(2,709)	(3,205)
Age^2		15	24
		(31)	(35)
Age missing		-81,724	-105,956
		(71,153)	(76,449)
Undergrad student			-26,530
			(37,294)
Graduate student			-5,703
			(29,312)
University Alumni			9,195
			(13,567)
University Employee			-24,723
			(20,403)
Observations	820	820	820
R-squared	0.886	0.898	0.899

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

a. All variables are binary indicator variables unless otherwise noted

Table A2. Full Regression Results: Effects of Individual Characteristics and Hazard Familiarity on Post-leak Home Price Responses (dev variable-= $price_{hi}$).

VARIABLES	(M)	(N)	(O)	(P)
Public Water	296,467***	272,593***	281,106***	277,462***
	(53,690)	(55,382)	(54,844)	(54,593)
× *1 ppb*	3,169	5,898	4,903	4,689
	(14,020)	(14,003)	(13,979)	(14,024)
× *4 ppb*	-6,475	-9,308	-14,229	-14,670
	(16,535)	(16,402)	(16,655)	(16,688)
× *6 ppb*	-45,586***	-43,869**	-47,372***	-47,688***
	(16,931)	(17,632)	(17,660)	(17,675)
× *9 ppb*	-65,227***	-61,301***	-61,775***	-61,831***
	(17,257)	(17,258)	(17,283)	(17,346)
Private Well	283,055***	259,143***	268,169***	264,222***
	(55,947)	(57,197)	(56,122)	(55,817)
× *1 ppb*	-19,597	-16,651	-15,394	-15,275
	(19,367)	(19,153)	(18,878)	(19,016)
× *4 ppb*	-14,860	-13,741	-12,770	-13,242
	(16,189)	(16,156)	(15,521)	(15,497)
× *6 ppb*	-45,842**	-46,537**	-49,032**	-48,764**
	(22,389)	(21,996)	(21,252)	(21,339)
× *9 ppb*	-83,996***	-84,612***	-85,535***	-85,598***
	(21,020)	(20,988)	(20,820)	(20,891)
Well with Filter	297,903***	275,862***	281,295***	278,626***
	(55,547)	(56,434)	(56,073)	(55,812)
× *1 ppb*	2,683	-71	2,284	2,736
	(15,539)	(15,560)	(16,657)	(16,775)
× *4 ppb*	-23,993	-25,786	-26,351	-26,223
	(16,678)	(16,493)	(16,583)	(16,432)
× *6 ppb*	-35,352**	-36,237**	-36,349**	-36,099**
	(17,334)	(18,173)	(18,297)	(18,262)
× *9 ppb*	-1,988	-2,788	-4,021	-4,422
	(16,193)	(15,857)	(15,905)	(15,793)

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Table A2. Full Regression Results: Effect of Individual Characteristics and Hazard Familiarity on Post-leak Home Prices Responses (continued).

VARIABLES	(M)	(N)	(O)	(P)
		--- Continued from Previous Page ---		
Bachelor's degree or higher	55,744***	52,507***	48,586**	48,017**
	(18,943)	(18,582)	(19,139)	(19,182)
Education Missing	5,831	8,628	3,276	3,658
	(54,939)	(54,780)	(56,151)	(57,046)
Has Children	-7,249	-5,264	-7,677	-8,689
	(15,853)	(15,861)	(15,949)	(15,867)
Has Children under 5 yrs	37,599***	38,265***	38,568**	39,810**
	(14,425)	(14,605)	(15,234)	(15,437)
Income (1 to 6 scale)	5,166	4,197	4,306	4,419
	(3,299)	(3,279)	(3,292)	(3,288)
Income Missing	-39,763	-42,409	-41,555	-41,613
	(35,786)	(35,277)	(36,139)	(36,223)
Age (years)	-1,866	-1,865	-1,860	-1,467
	(2,695)	(2,650)	(2,613)	(2,628)
Age^2	18	16	15	10
	(31)	(30)	(30)	(30)
Age missing	-79,838	-72,850	-80,245	-76,365
	(70,558)	(70,483)	(70,829)	(70,910)
Well Water	-14,987	-15,842	-13,807	-13,580
	(11,593)	(11,636)	(11,887)	(11,857)
Benzene		452	425	1,288
		(11,911)	(12,165)	(12,617)
Benzene Missing		18,851	25,886	23,596
		(33,392)	(35,551)	(35,444)
Parts-per-billion		39,187*	35,415*	33,637*
		(20,382)	(20,245)	(20,317)
LUSTs			6,626	6,404
			(15,223)	(15,199)
LUST in Neighborhood			-45,550**	-46,528**
			(21,041)	(21,304)
recent_in_mkt				-7,157
				(12,939)
Observations	820	820	817	817
R-squared	0.898	0.900	0.902	0.902

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

a. All variables are binary indicator variables unless otherwise noted

Appendix B. Sample Questionnaire.

Thank you for participating in this survey. By filling out this questionnaire, you are helping students get experience and training in survey research, and data collection and analysis. We appreciate your help.

This research is part of a dissertation project focusing on housing and environmental quality. We are interested in your opinions about and experience with these topics. There are no right or wrong answers to the questions in this questionnaire.

Please fill out this questionnaire to the best of your knowledge. It is anonymous, and all answers will be kept confidential.

You must be at least 18 years of age to participate in this survey.

If you have any questions, please feel free to contact the Student Investigator, Dennis Guignet, at the University of Maryland, dguignet@arec.umd.edu.

Section A. Your Current Home.

A1. Do you currently live in Maryland?

1. ❒Yes
2. ❒No

If Yes, what County do you live in? ____________________________

If No, what State do you live in? ____________________________

A2. Which of the following best describes your neighborhood?

1. ❒ Rural
2. ❒ Suburban
3. ❒ Urban

A3. What best describes the type of home you live in?

1. ❒ Single family, detached
2. ❒ Townhouse, or duplex
3. ❒ Apartment or condominium in a multi-family building
4. ❒ Other: ______________________________

A4. Which of the following best describes your situation?

1. ❒ I, or someone in my family, own my home
2. ❒ I, or someone in my family, rent my home
3. ❒ Other rental or free housing situation, please explain:__________________

A5. Approximately how long have you lived in this home?

_________________________ years

Section B. The Water at Your Home.

B1. Where does the water at your current home come from?

1. ❒ Public Water System
2. ❒ Private Groundwater Well
3. ❒ I don’t know

B2. Have you ever lived in a home where the water came from a private groundwater well?

1. ❒ Yes
2. ❒ No
3. ❒ I don’t know

B3. Has the drinking water at your home ever been tested?

1. ❒ Yes
2. ❒ No

B4. Did the test results indicate that there was a water quality problem?

1. ❒ Yes, and the problem was:

   ____

2. ❒ Yes, but I do not remember the details of the problem
3. ❒ No problem was found
4. ❒ I never had my water tested

Section C. Background Information.

C1. Have you ever heard of any of these contaminants in groundwater or drinking water?

1. Arsenic...........................❒ Yes ❒ No
2. Coliforms........................❒ Yes ❒ No
3. Benzene.........................❒ Yes ❒ No
4. Lead...............................❒ Yes ❒ No
5. Trichloroethylene...........❒ Yes ❒ No
6. Xylenes...........................❒ Yes ❒ No

C2. Have you ever heard of the term "parts per billion"?

1. ❐ Yes
2. ❐ No

"**Parts per billion**" (or ppb) is a measure of the concentration (or amount) of a substance in water.

For many pollutants, the law specifies a standard—a concentration level that must not be exceeded in drinking water.

- Standards are set to protect human health with a wide margin of safety.
- Standards are often reported in ppb.

For example, the standard for benzene is 5 ppb.

C3. Sometimes contaminants leak from underground tanks. Have you ever heard of the term 'Leaking Underground Storage Tank'?

1. ❐ Yes
2. ❐ No

Underground storage tanks are

- Used to store petroleum products
- Commonly found at gas stations.

Occasionally these tanks can leak due to rusting and cracks and can contaminate the surrounding soil and groundwater.

Benzene is the typical pollutant from these leaks, and is a known carcinogen.

C4. Are you aware of any homes in your neighborhood or city/town that were contaminated because of a leak from an underground storage tank?

1. ❐ Yes
2. ❐ No

Section D. A Neighborhood in Maryland.

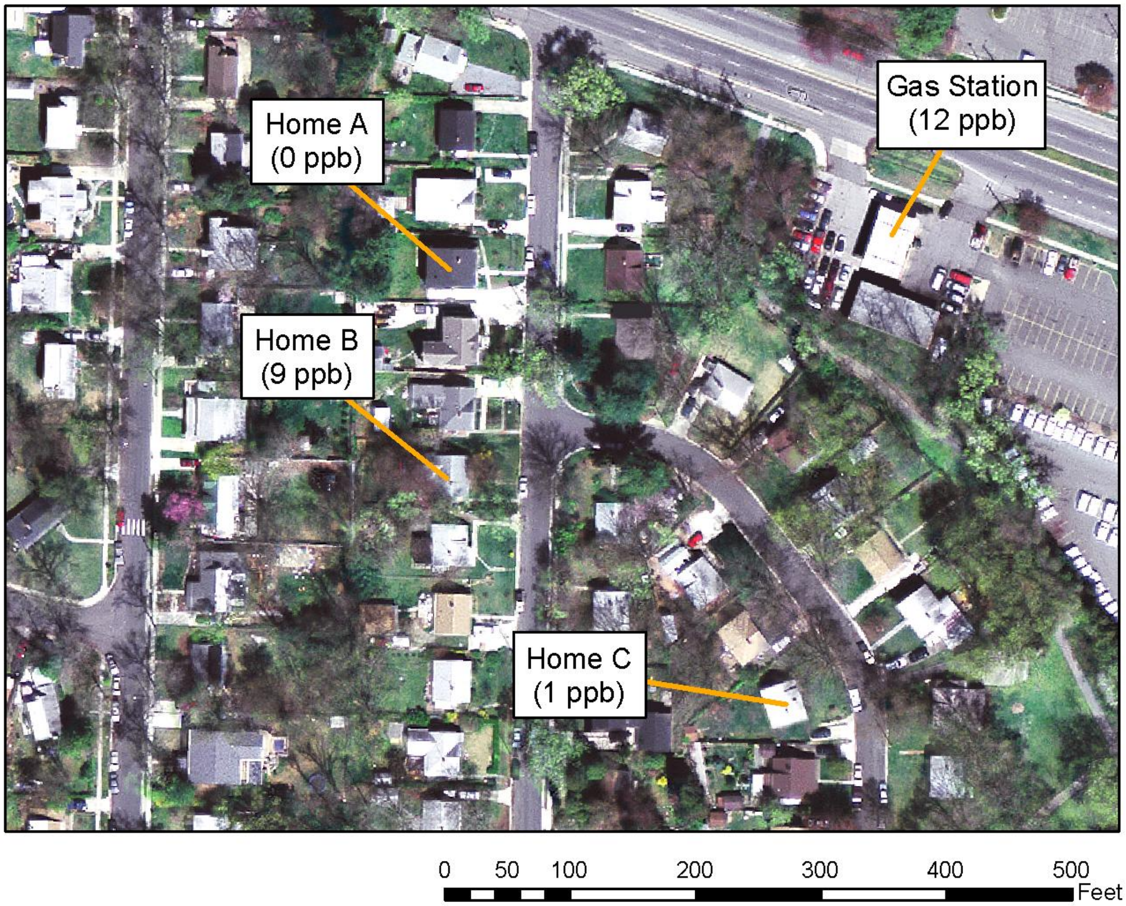
Here is an aerial photo of a neighborhood in Maryland.

D1. **Based on this photo, how similar is this neighborhood to the one you live in?** Please rate this neighborhood on a scale from 1 to 5, where 1 = very different from my neighborhood and 5 = very similar to my neighborhood.

Very different from my neighborhood				Very similar to my neighborhood
❐ 1	❐ 2	❐ 3	❐ 4	❐ 5

In this neighborhood the homes are worth $400,000 on average, and are served by the public water supply system, which gets its water from a distant reservoir.

Now suppose a leak occurs at one of the tanks at the gas station in the neighborhood. The leak has been stopped, but no cleanup has been undertaken. The groundwater around the site is tested for benzene and the test results for three of the homes are shown in the photo below.



D2. How much do you think each of these homes will sell for after this leak? Please enter your best guess if you are unsure.

Home A: $___________________________

Home B: $___________________________

Home C: $___________________________

Section E. Socio-demographic Questions

E1. Which of the following best describes your relationship with the University of Maryland?

1. ❐ Undergraduate Student
2. ❐ Graduate student
3. ❐ Alumnus/a
4. ❐ Employee
5. ❐ Friend of the University
6. ❐ Other: ______________________________

E2. How many children/teenagers aged 0-18 live in your home?

______________________ children/teenagers

How many of these children are less than 5 years old?

______________________ children

E3. What is the total annual income for your household before taxes? Please include all sources of income.

1. ❐ Less than $35,000
2. ❐ $35,000-44,999
3. ❐ $45,000-54,999
4. ❐ $55,000-74,999
5. ❐ $75,000-99,999
6. ❐ $100,000-149,999
7. ❐ $150,000-199,999
8. ❐ $200,000-250,000
9. ❐ More than $250,000

E4. What is your age?

__________________________ years

E5. What is the highest level of schooling you have completed?

1. ❐ Some high school
2. ❐ High school diploma
3. ❐ Some college
4. ❐ Associate degree
5. ❐ Bachelor's degree
6. ❐ Post graduate education

E6. Before we finish this questionnaire, we would like to know if you have bought a home, sold a home, or have been seriously looking to buy or sell a home in the last 5 years. Please check all that apply.

1. ❐ Yes, I bought a home
2. ❐ Yes, I sold a home
3. ❐ Yes, I have been seriously looking to buy/sell but did not buy/sell
4. ❐ None of the above

You have reached the end of the questionnaire.
Thank you very much for your responses and your time.

Chapter 4: Can Property Values Capture Changes in Environmental Quality? Evidence from a Stated Preference Study in Italy and the UK

By: Dennis Guignet and Anna Alberini

I. Introduction

Hedonic property value models are a popular method for placing a value on environmental quality and other localized amenities and disamenities. This approach assumes that changes in environmental quality are captured into property prices if the flow of housing services is affected by such changes. Rosen (1974) demonstrates that at equilibrium one can infer marginal welfare effects from changes in property values, and in some cases we can even estimate non-marginal welfare effects solely from the hedonic price surface (Palmquist, 2005).

Given well-behaved housing markets with sufficiently frequent transactions it is, in theory, relatively straightforward to estimate the extent to which the changes in environmental quality are capitalized in real estate prices. One simply estimates regressions where home prices (or some monotonic transformation of prices, such as the log of price) are regressed on structural characteristics of the dwelling (e.g., square footage, number of floors, variables capturing construction quality and style), neighborhood characteristics (e.g., distance from the city center, crime), and measures of environmental quality at the time the home was sold. Depending on the specifics of the study, the latter set of variables is often replaced with distance to a localized amenity or disamenity (Boyle and Kiel, 2001; Farber, 1998). After controlling for everything else, the coefficient(s) on the environmental quality measure(s) is used to infer the welfare effects of a change in environmental quality.

Elegant and appealing as this approach might be, in practice it is fraught with difficulties. For starters, if the environmental quality measure is correlated with other omitted characteristics of a home or neighborhood, then the estimated marginal implicit prices may end up capturing the latter's effects on property values. Therefore an analyst could falsely attribute changes in property values to shifts in environmental quality. This omitted variable concern has led some researchers to rely on exogenous shocks for identification (e.g., Chay and Greenstone, 2005; Greenstone and Gallagher, 2005; Hallstrom and Smith, 2005; Pope, 2008; Horsch and Lewis, 2009).

Second, researchers typically assume, without testing, that markets respond to objective measures of environmental quality (e.g., the readings from air quality monitors, as in Chattopadhyay, 1999, or risk assessments, as in Gayer et al., 2000, 2002), when in reality people—and hence housing markets—are either unaware of these measures, or respond to something else entirely. In principle, this problem can be circumvented if it is possible to ask people what their perceived environmental quality level was when they bought or sold their home, but to our knowledge this has not been attempted in the literature.[72]

Alternatively, one might ask homebuyers or sellers what the price of their home would be if environmental quality changed to an extent that is clearly specified to them. There have been only a few applications of this stated preference approach. Earnhart (2001, 2002) used it in conjunction with actual housing transactions to infer the value of proximity to open space. Chattopadhyay et al. (2005) deployed it to

[72] McClelland et al. (1990) have residents (not necessarily people who recently purchased a home) in a "neighborhood" assess their beliefs of the safety risk posed by nearby hazardous waste sites. These aggregated neighborhood risk belief measures were included in the hedonic model, and found to be negatively correlated with prices.

estimate the effect of reducing pollution at one of the Great Lakes, and Phaneuf et al. (2010) combine stated preference and actual housing sale data in a GMM framework to assess cleanup of the Buffalo River in Buffalo, NY. Jenkins-Smith et al. (2002) examine information disclosure about contaminants from a smelter in Corpus Christi, TX, and elicit respondents' willingness-to-pay (WTP) and willingness-to-accept (WTA) for a hypothetical home. Simons and Winson-Geideman (2005) did a contingent valuation study asking people how much they would buy a hypothetical home for under three alternative scenarios regarding knowledge and severity of groundwater and soil contamination.

In all of these earlier studies environmental quality was defined qualitatively, and we believe that it remains unclear how respondents interpret such subjective measures. For example, Chattopadhyay et al. mention "reducing pollution" in a more or less complete way, and even envision hypothetical scenarios where pollution would be made worse, but there are no rigorous measures of pollution used in their survey, and respondents are simply asked to think that their house is closer to or farther from a more or less heavily polluted lake. A similar approach is followed in Phaneuf et al. (2010).

In this paper we report the results of a stated preference study where we asked people to choose between homes that differ from each other in two attributes—the health risks associated with air pollution levels at a home's location and its price. The health risks were couched as reductions in the risk of dying from specified causes linked with air pollution exposures (e.g., an X in 1,000 decrease in the probability of dying). To our knowledge, this is the first stated preference study in the housing context with clearly specified mortality risks.

We wish to investigate four research questions. First, are people willing to trade off mortality risk reductions for a change in the cost of their home? Second, if so, what is the value of a statistical life (VSL) we can infer from their responses? Some notable hedonic studies (Gayer et al., 2000, 2002; Davis, 2004) examine how home values are affected by environmental health risks, and under the necessary (but untested) assumption that home buyers and sellers are explicitly aware of these risks, the researchers infer the value of a statistical case of cancer avoided. In our stated preference study we need not assume respondents are aware of the health risks, we *know* they are aware since risks are explicitly presented.

Our third question examines how respondents' perceptions of air pollution where they live, its effects on their health, and their perceived ability to personally reduce health risks, influence their WTP. Fourth, we examine whether there is any systematic heterogeneity in respondents' WTP for reduced mortality risks based on socio-economic characteristics, the city in which they live, and recent experience in buying a home.

To answer these questions we administered an on-line questionnaire to a representative sample of persons aged 40-60 in 16 cities across Italy and the United Kingdom (UK) in August and September 2010. We find that the stated choices made by our Italy survey respondents are consistent with VSL figures of €1.313-5.775 million, depending on whether they rent or own their home, and the cause of death. In the UK, we found that renters did not place a positive value on risk reductions, whereas the VSL for homeowners was €1.828 million (2010 PPP euro). These figures are reasonable and well within the typical VSL range judged acceptable in the risk and safety literature (Viscusi and Aldy, 2003). They are also consistent with our own previous work in these countries (Alberini et al., 2006; Alberini and Chiabai, 2007a, 2007b; Alberini et al., 2007; Alberini and Ščasný, 2011a).

The differences between the Italy and the UK VSL figures are due in part to differing perceptions of the local air quality: While the Italy respondents expressed concern about air pollution where they live and its effects on their health, the UK respondents did not seem as concerned. Our econometric results confirm that people who perceive air pollution in their city to be more threatening tend to value a mortality risk reduction much more. We also find heterogeneity in homeowners' WTP for a risk reduction based on some socio-economic characteristics, beliefs regarding government responsibility for mortality risk reductions, the value of their home, and at least in the UK, the city in which they live.

The remainder of this paper is organized as follows. We provide a review of the literature in section II to motivate our analysis. We then describe the study design and housing choice questions in section III. Section IV presents the econometric model. Section V describes the data. Section VI presents the estimation results. Section VII concludes.

II. Literature Review

II.A. The Value of A Statistical Life

The Value of a Statistical Life (VSL) is a summary measure of people's Willingness to Pay (WTP) for a reduction in mortality risks, and is commonly used in benefit-cost analyses of public programs (Appelbaum, 2011). The VSL is basically the marginal rate of substitution between income and the probability of dying, holding utility constant, and can therefore be interpreted as the marginal value of a reduction in mortality risks (see section IV.B for the formal definition). Alternatively, one can interpret the VSL as the amount society is willing to pay to save the life of a generic person (Freeman, 1999, pg. 321).

Since there is no explicit markets for health risks, researchers have developed several revealed and stated preference approaches to estimate the VSL. In revealed preference methods researchers infer the VSL from peoples' behavior in markets for goods that are at least partially characterized by changes in mortality risks. For example, in the labor market researchers examine the compensation required for workers to accept riskier jobs, all else constant (e.g., Viscusi, 1993; Viscusi and Aldy, 2003; and Aldy and Viscusi, 2007). Similar methods have been used in automobile markets to analyze the premium for vehicles with additional safety features (Andersson, 2005), and in housing markets for homes in neighborhoods with decreased cancer risks from pollution (Gayer et al., 2000, 2002; Davis, 2004).

A key assumption in these revealed preference studies, which is one of the underlying concerns discussed throughout this dissertation, is whether buyers and sellers in these markets are explicitly aware of, and correctly perceive, the objective health risks specified in the econometric models. Stated preference methods provide an opportunity to elicit preferences for a risk reduction when we *know* respondents are aware of the objective risks, because they are explicitly given to them as part of the study design. Stated preference methods have been used to elicit people's WTP for risk reductions in a variety of contexts, including transportation and road safety (e.g., Perrson et al., 2001, Bhattacharya et al., 2007), contaminated site cleanup (Alberini et al., 2007), and risks from power generators (Itaoka et al., 2006), amongst others.

Conjoint choice experiments are one stated preference approach for estimating the VSL. In these exercises respondents choose among hypothetical goods or public programs that are defined by several attributes, including cost and health risks. In choosing a product respondents inherently trade off money and mortality risks, and so from these responses researchers can infer the VSL.[73]

In this dissertation chapter, I use a conjoint choice framework where respondents choose between hypothetical variants of their home, with varying costs and mortality risks associated with local air pollution levels (see section III). We chose the conjoint choice framework because it simulates the discrete home choices people make in the actual market. While there has been several revealed preference studies analyzing how home values are affected by air pollution and health risks, I argue that (i) omitted variable bias and (ii) peoples' awareness of the assumed environmental quality measures, are of particular concern in these contexts.

[73] See Alberni and Šcasný (2011a, 2011b), Tonin et al. (2009), Alberini et al. (2007), Itaoka et al. (2006), Tsuge et al. (2005) for some recent examples of conjoint choice experiments estimating the VSL.

II.B. Hedonic Property Value Models: Health Risks and Air Pollution

Boyle and Kiel (2001) review 12 hedonic studies of the effects of air pollution on home values, starting with Ridker and Henning's (1967) seminal piece. Nine of the studies reviewed suggest a negative correlation between home prices and air pollution levels, but the results are in general mixed across studies and depend greatly on how air pollution is measured. Boyle and Kiel believe that one reason for the mixed results is that the air quality measures may be correlated with unobserved variables.

One way to get around this problem is to find a location with exogenous shocks in air pollution that are sustained long enough for the housing market to react to them. Chay and Greenstone (2005) devise a quasi experiment that exploits the discrete relationship between compliance and non-compliance status under the Clean Air Act, and air pollution regulations. They implement instrumental variables, regression discontinuity, and matching techniques, and conclude that improved air quality does lead to an increase in home values, at least as reflected by median county-level home prices.

The second practical difficulty in implementing hedonic property value methods is that researchers typically assume that markets respond to objective measures of environmental quality. Although such assumptions are often necessary, analysts rarely (if ever) test how buyers and sellers in the housing market perceive these measures, or if they are even aware of them at all. "It is possible that measures of air quality generally included in these [hedonic] studies may not be the measures relevant to homeowners (Boyle and Kiel, 2001, pg140)." For example, Chattopadhyay (1999) studies how home prices in Chicago are affected by particulate matter and sulphur dioxide pollution. He uses pollutant level readings from air quality monitoring stations. However, it is unlikely that residents are aware of these readings, and it is unclear whether these readings are a good proxy for the pollution measure that matters to homeowners.

Gayer et al. (2000, 2002) analyze home values around a Superfund site in Grand Rapids, MI. Using a dilution and dose-response model they estimate the household specific excess cancer risk posed by the site. Under the assumption that home buyers and sellers are explicitly aware of these risks, they infer a value per statistical cancer case (VSCC) avoided of $3.9-8.3 million. Similarly, Davis (2004) examines how home prices are affected by an unexplained cancer cluster in Churchill County, NV. Using various measures of the cancer risk, he infers a value to avoid a statistical case of pediatric leukemia of $3.0-9.2 million. Although these studies provide unique and novel contributions to the non-market valuation literature, they inherently assume that home buyers and sellers are aware of these health risks and perceive them correctly. This is an assumption that is untested and may be unwarranted, especially for low probability events such as morbidity and mortality (see Viscusi, 1998).

II.C. Stated Preference Studies on Property Values

An alternative non-market valuation approach is to design a stated preference study where one might ask homebuyers or sellers what the price of their home would be if environmental quality changed to an extent that is clearly specified to them. Furthermore, in a stated preference study the researcher can construct a clean experimental design, where there are no confounders, in order to properly identify the effects of an environmental good on home values.[74]

There are only a few stated preference studies that focus on home values in order to estimate the value of an environmental good. Earnhart (2001, 2002) used it in conjunction with actual housing transactions to infer the aesthetic value residents place on different types of environmental amenities near their home (e.g., a backyard, open field, lake, forests). Respondents were asked to choose between hypothetical homes which varied in terms of the environmental amenity, number of bedrooms and bathrooms, interior space, age of the home, lot size, flooding frequency, construction style, and price. The environmental amenity was conveyed to survey respondents using actual photos of these natural features. Chattopadhyay et al. (2005), Jenkins-Smith et al. (2002), Phaneuf et al. (2010), and Simons and Winson-Geideman (2005) conduct stated preference studies analyzing how home values are affected by environmental disamenities (see section II.D in chapter 3 for details).

In all of these earlier stated preference studies environmental quality was defined qualitatively. It is our judgement that the change in environmental quality was not clearly defined to the respondent, and it remains unclear how respondents interpret such subjective measures. For example, Chattopadhyay et al. (2005) mention "reducing pollution" to a more or less complete extent, and even envision hypothetical scenarios where pollution would be made worse, but there are no rigorous measures of pollution used in their survey, and respondents are simply asked

[74]Of course these advantages stem from the hypothetical nature of stated preference exercises. The primary criticism against this technique is that what people say in a hypothetical situation may not reflect their true actions (Freeman, 1993, pg. 176).

to think that their house is closer to or farther from a more or less heavily polluted lake.

In this paper, we report the results of a stated preference study where we asked people to make choices between homes that differ from each other in two attributes—the health risks posed by air pollution in the area where the home is located, and price. The health risks were couched as reductions in the risk of dying from specified causes linked with air pollution exposures.

To our knowledge, this is the first stated preference study in the housing context with clearly specified mortality risks. Our approach is different from that used by Chanel and Luchini (2008), where respondents are asked to indicate which of two *cities* they would move to (together with their household), the cities being identical in all aspects (size, housing, weather, public services, etc.), except for the cost of living and air pollution. These authors expressed health risks as follows: "One person out of 100 randomly chosen in the street is likely to die before 80 due to poor health related to air pollution exposure. This person will have lost around 10 years of life."

Although Chanel and Luchini's wording is consistent with epidemiological evidence about air pollution (where results are typically expressed in loss of life expectancy) and introduces uncertainty by mentioning a random person, it is unclear how the respondents interpreted this statement, and it takes an extremely complicated model to infer the Value of a Statistical Life Year.

Van Houtven et al. (2008) examine how individuals trade off different types of mortality risks. They ask respondents to choose between two locations that are exactly the same except in terms of automobile and cancer mortality risks. In contrast to our study, cost is not an attribute of the locations. Van Houtven et al. do not estimate a VSL per se; instead their interest lies in estimating how to adjust existing VSL estimates by investigating peoples' willingness to trade off different types of mortality risks, namely automobile accidents versus different types of cancers. They conclude that people value reductions in the risk of dying from cancer up to three times more than that of dying in an automobile accident, but this effect declines as the cancer death latency period increases.

III. Questionnaire and Study Design

III.A. Questionnaire Structure

To investigate how much people value mortality risk reductions in the air pollution-housing context, we developed a number of questions about the respondent's home and neighborhood, perceptions of air quality where he or she lives, and housing choices under hypothetical but clearly specified conditions. We placed them in the middle (section K) of the broader EXIOPOL mortality risk valuation questionnaire (see Alberini and Ščasný, 2011b), Since the housing choice section came right after the probability tutorial, education about mortality risks and conjoint choice questions about mortality risks reductions, we argue that by the time respondents started the home choice valuation questions, they were well informed about mortality risks and risk-reducing measures, and that they understood that risk reductions usually come at a cost.

We begin the section by asking the respondents to indicate the type of home they live in (e.g., single-family home, etc.), the size of the home (i.e., the number of rooms), whether they own or rent it, how long they have lived at that home, and how much longer they plan to continue living there.[75] We also elicit the monthly rent for those that rent their home, and the value of the home in today's housing market for those who own their home.

Because in our choice questions respondents will face tradeoffs between money and health risks due to air pollution, we next inquire about the respondent's perception of the level of air pollution in his or her neighborhood. We offer five response categories ranging from very low to very high. We also ask respondents to indicate their degree of agreement or disagreement with four statements about air pollution: (i) "The air pollution where I live could eventually have harmful effects on my health," (ii) "I am aware of my local air pollution levels," (iii) "People can personally do things to lower the health risks from air pollution," and (iv) "I am physically sensitive to air pollution."

Finally, we present our hypothetical choice scenario, which is accompanied with a brief explanation that (i) air pollution is an environmental risk to human health, (ii) even low concentrations may have adverse health effects (such as cardiovascular and respiratory diseases), and (iii) air pollution may reduce lung function, make individuals more susceptible to respiratory infections and even cause cancer.

III.B. Study Design.

Each respondent answers two housing choice questions. Our respondents are asked to imagine that they are looking for a new home, and that they have identified

[75] The purpose of the latter two questions was to determine whether the respondent is acquainted with the current housing market—as a recent buyer or a potential seller. We reason that the better the familiarity with the housing market, the more reliable the choice responses.

two homes that are almost identical for the feel of the neighborhood, size, number of bedrooms and bathrooms, and all other characteristics. The only differences between the two homes are (i) the risk of dying attributable to air pollution, relative to that of the current home, and (ii) the price or rent of the home.

In the first choice question, the respondent must choose between home A, where risk and price are the same as their current home, and home B, which is in an area with better air quality, and hence lower mortality risks, but is more expensive. In the second choice question, the respondent must choose between two different homes—both are located in neighborhoods with lower levels of air pollution, and thus the health risks are lower than the current home, but both are also more expensive than the current home. It is clear that both choice questions ask respondents to trade off mortality risk reductions for income. The risk reductions were expressed as X in 1000 over 10 years. Costs were presented as an increase relative to one's current home (e.g., X euro more than your current home). Respondents who currently rent their home faced tradeoffs between risk reductions and rent. We expressed rent on a per month basis, but respondents could also view this cost in annual terms. For homeowners, we provided a premium on the price of the new home relative to the value of their current home, and then showed its annual equivalent (based on 10 years).

To create our experimental design, we began with specifying a vector of four possible risk reductions, namely 2, 3, 4 and 5 in 1000 over 10 years (equivalent to 2, 3, 4, and 5 in 10,000 for one year), and a vector of five possible "price differential" levels (250, 500, 1000, 1800 and 3000 euro per year, for a total of 10 years).[76] Mirroring the rest of the questionnaire, the risk reductions would apply to the respondent but not to any other family members or any other person.

In the first housing choice questions, home A was the same as the respondent's current home, and so the risk reduction and price differential with respect to it were zero. Home B was selected at random from the 20 possible combinations of risk reductions and price differentials mentioned above. For the second housing choice questions, we created a total of 120 pairs. One of the homes in these pairs was selected at random from the 20 possible combinations listed above. The other home for each pair was selected from the remaining, non-dominated combinations. Respondents were assigned at random to one of these 120 pairs. The responses to these questions are then used to estimate the model outlined in the next section.

IV. The Model.

IV.A. Theoretical Motivation.

Suppose an individual is considering moving to a new house (home *j*) that consists of the bundle of attributes $(\boldsymbol{x}_j, R_j)$, where $\boldsymbol{x}_j$ denotes all characteristics of the home (e.g., number of bathrooms, interior square footage, lot size) and neighborhood (e.g., public parks, school quality, crime), and R_j, which is an individual's risk of dying. Mortality risk is part of the housing bundle because environmental factors at

[76] For the UK the costs were converted to British Pounds, and presented as such to those respondents.

the location of home *j*, such as air quality, may affect one's health, and in turn their risk of dying. The expected indirect utility of home *j* to individual *i* is:

$$V_j = V(\boldsymbol{x}_j, R_j, y - C_j) = (1 - R_j)u(\boldsymbol{x}_j, y - C_j) + R_j v(\boldsymbol{x}_j, y - C_j) \qquad (1)$$

where C_j is the cost of home *j*, *y* denotes an exogenous level of income, $u(\cdot)$ is the level of utility experienced if the individual does not die and $v(\cdot)$ is the utility level realized if an individual does die. The housing attributes and cost of home *j* can be expressed in terms of the difference relative to one's current home (x_0, R_o), and, assuming $V(\cdot)$ is linear, we can re-write equation (1) as:

$$V_j = \gamma(\boldsymbol{x}_0 + \Delta\boldsymbol{x}_j) + \alpha(R_0 + \Delta R_j) + \beta(C_0 + \Delta C_j) \qquad (2)$$

where C_0 denotes the cost of the current home, and $\Delta\boldsymbol{x}_j$, ΔR_j, and ΔC_j are the differences between the home and neighborhood characteristics, mortality risk, and costs, respectively, between home *j* and the current home. Parameters γ, α, and β are unknown coefficients.

IV.B. Empirical Model.

We posit that the responses to the choice questions in this survey are driven by an underlying random utility model (RUM). Therefore individual *i* will choose home alternative *k* at choice occasion *t* if

$$V_{ikt} + \varepsilon_{ikt} \geq V_{ijt} + \varepsilon_{ijt}\ , \ \ \forall\, j = 1, \dots, J \qquad (3)$$

where *J* is the number of alternative homes (including home *k*) in the choice set. The error term ε_{ijt} captures aspects of the utility that are known to the respondent but not to the researcher. This random component is assumed to be an i.i.d. draw from a type I standard extreme value distribution.

Plugging the deterministic aspect of utility from equation (2), and cancelling out common terms, the inequality in (3) can be rewritten as

$$\alpha \Delta R_{ikt} + \beta \Delta C_{ikt} + \varepsilon_{ikt} \geq \alpha \Delta R_{ijt} + \beta \Delta C_{ijt} + \varepsilon_{ijt}\ , \quad \forall\, j = 1, \dots, J \tag{4}$$

In this study we do not vary characteristics of the home and neighborhood across alternatives, therefore $\Delta \boldsymbol{x}_{ikt}$=0 and drops out of equation (4). The scalar ΔR_{ikt} is the mortality risk reduction made possible by living in home k relative to one's current home, and ΔC_{ikt} is the price premium that must be paid relative to the value of the current home. The coefficients to be estimated are the marginal utility of a unit risk reduction (α) and the marginal utility of income (-β).

We present respondents with two different choice questions or occasions (t=1, 2). Each choice question contains two alternative homes (J=2), home A and home B. In the first choice question home A is the same as the respondent's current home, so ΔR and ΔC are both zero for home A, and are different from zero for home B. In the second choice question, ΔR and ΔC are different from zero for both home A and home B.

Since we assume that the random component of utility follows a type I standard extreme value distribution, the probability of choosing home *k* is:

$$\pi_{ikt} = exp(\alpha \Delta R_{ikt} + \beta \Delta C_{ikt}) / \textstyle\sum_{j=1}^{2} exp\big(\alpha \Delta R_{ijt} + \beta \Delta C_{ijt}\big). \tag{5}$$

Assuming that the error terms are independent within and across respondents, the log likelihood of the sample is:

$$\log L = \textstyle\sum_{i=1}^{n} \sum_{t=1}^{2} \sum_{k=1}^{2} \pi_{ikt} \tag{6}$$

where *n* denotes the total number of respondents.

Coefficients α and β are estimated by maximum likelihood. We expect the marginal utility from a reduction in mortality risk (α) and the marginal utility of income (-β) to be positive. The Value of a Statistical Life (VSL) is estimated as $(\hat{\alpha}/\hat{\beta}) \times (-1000)$. Multiplication by 1000 is necessary because we express risk reductions as X (per 1000) rather than 0.00X.

We estimate model (5) separately for Italy and the UK, and for owners and renters within each country. Equations (2)-(5) assume that the marginal utilities are constant across all individuals. We relax this assumption by including in the indirect utility and the econometric model interactions between the risk reduction and price premium with individual characteristics of the respondent, such as gender, age and income. We also enter interactions with the perceived seriousness of the air pollution problem at the locale where the respondent lives.

V. The Data

The survey questionnaire was administered over the internet to persons aged 40-60 in Italy and the UK in August and September 2010.[77] We collected a total of 2426 completed questionnaires in the UK and 2369 in Italy. The samples were comprised of an even number of men and women, and were nationally representative for education and income of the Italy and UK populations in that age group.

In both countries, the respondents were drawn from the residents of cities selected to ensure geographical and air quality representativeness. The number of

[77] These persons belong to a panel of consumers assembled and maintained by IPSOS, a large survey firm with headquarters in Paris. We used the IPSOS Office in Prague, Czech Republic.

respondents from each city is shown in table 1. Based on our sampling scheme the majority of UK respondents were from London (40.5%). Most of the Italian sample consisted of individuals from Milan (26.6%) and Rome (21.7%).[78]

Descriptive statistics of the samples are reported in table 2. As per our sampling plan, the two samples are similar in terms of gender and age. They are also remarkably similar in terms of perceived health status. Homeownership, on the other hand, is slightly more prevalent in the Italy than the UK sample (78% v. 69%). The Italy respondents are also slightly more likely to have a college degree (26% v. 22%), but annual household income is higher in the UK (mean= €39,377 euro, median= €34,178) than in Italy (mean= €32,392, median= €27,500) (all income figures are in 2010 PPP euro).

Regarding marital and family status, about three quarters of the Italian respondents are married v. two-thirds in the UK. Seventy-four percent of the Italian respondents and 67% of the British respondents have children.

In table 3, we compare homeowners and renters in each of the two countries. Univariate t-tests reveal that in both samples, homeowners are wealthier, more highly educated, and more likely to be married and have families.

In figure 1 we compare the perceptions of air pollution and associated health risks across the two countries. Clearly, the Italy respondents report the air quality in their city or neighborhood to be much worse than their UK counterparts. The Italians are also more likely to agree with the statement that air pollution can be harmful to one's health, they are more aware of their local air quality, are more likely to agree

[78] Note that seven British and nine Italian respondents did not report what city they currently live in.

that "people can do things to protect themselves from air pollution," and report being more physically sensitive to air pollution

As shown in tables 4.a and 4.b, virtually everyone answered the housing choice questions. Only one respondent in the UK and one in Italy failed to answer. In Italy, 49.56% of the respondents chose home A (the one that is identical for risks and cost to the respondent's current home) in the first housing choice question, and 52.43% chose home A in the second housing choice question. In the UK, home A was chosen by 59.52% of the subjects in the first housing choice question and by 52.47% of the respondents in the second housing choice question. Taken together, these statistics suggest that the UK respondents place a lower value on risk reductions than their Italian counterparts. The variation in responses suggests that in this stated preference context people are willing to make tradeoffs between mortality risks and the cost of their home.

VI. Estimation Results

Estimation results for the base models are reported in table 5 for Italian homeowners and renters, and in table 6 for their UK counterparts. In table 5, model A shows that homeowners in the Italy sample trade off risks for income at a rate consistent with a VSL of €5.775 million euro. The corresponding figure for renters is €1.313 million (model B). In both groups, the marginal utility of a risk reduction and that of income are positive and significant, implying that the responses to these valuation questions do pass the "scope" test. In other words, as predicted by economic theory, the larger the risk reduction, the more people are willing to pay for it.

As shown in table 6,the UK homeowners' VSL is only one third of the Italians--€1.828 million (PPP euro). Unlike the Italians, British renters, on average, are insensitive to the size of the risk reductions shown to them, and in fact they do not seem to place a positive value on mortality risk reductions.[79, 80]

Our descriptive statistics show that the UK sample is certainly no less wealthy than the Italy sample, so we suspect that such differences in the valuation of risk reduction is due to either differences in perceptions of air pollution, and/or differences in beliefs about opportunities for reducing exposures. Figure 1 indeed suggests that the Italy and the UK samples were very different with respect to pollution perceptions.

In tables 7 and 8, we report the results of models where the risk reduction is interacted with dummies representing risk perceptions. For example, drisk_high is the risk reduction interacted with a dummy that takes on a value of 1 if the respondent believes air pollution levels in the city where he or she lives are high or very high. The variable drisk_harm is constructed in a similar fashion with the responses to the statement that "Air pollution can be harmful to my health," drisk_aware is an

[79] When focusing on the 205 (out of 752) renters in the UK who perceive air pollution levels in the city where they live as high or very high, we estimate a VSL of €2.191 million.

[80] As a robustness check we ran variants of models (A) and (B) in tables 5 and 6 that include an indicator variable denoting home A. The coefficient estimates on this dummy variable were generally insignificant, indicating that conditional on risk and cost the respondents were not more likely to choose one alternative over the other. However, for the Italian homeowners this coefficient was positive and statistically significant at the 5% level, suggesting that respondents in this subsample were systematically more likely to choose the left-most alternative (home A), all else constant. This result only held for the second choice question, where home A was randomly assigned a hypothetical change in mortality risks,, and omitting the alternative-specific intercept did not meaningfully change the estimates of α and β.

interaction with the strong or very strong agreement that the respondent is aware of local pollution levels, drisk_lower is based on agreement that people can personally do things to lower the health risks from air pollution, and drisk_sensitive uses the responses to the statement that the respondent is physically sensitive to air pollution.

For simplicity, attention is restricted to homeowners. When the abovementioned interactions are entered one at a time in the model, they are generally positively and significantly associated with the VSL. For example, believing that air pollution is serious implies a VSL that is over €6 million and €3.8 million higher than the rest of the sample of the Italy and UK homeowners, respectively.

In tables 9 (Italy) and 10 (UK), we present the results of three specifications. The first, labelled as (A), includes interactions between the risk reduction and cost with individual characteristics of the respondents. The second specification (B) includes interactions between risk reductions and risk perceptions, and the third (C) enters an interaction between the risk reduction and a dummy variable equal to one if the respondent believes that the government is responsible for reducing mortality risks from cancer and heart disease. Again, attention is restricted to homeowners.

Starting with table 9 (Italian homeowners), in Italy persons with higher education levels place a higher value on risk reductions. For example, in the Italy sample, all else the same a respondent with a college degree has a VSL that is €4.70 million higher than someone without college degree. Table 10 shows that in the UK, the coefficient on the risk reduction interacted with college degree is also positive, but not statistically significant. At about one million euro, the magnitude of this effect (if we ignore for the moment the fact that this coefficient is not statistically significant) is smaller than that for Italy.

Gender is somewhat important in the UK, but not in Italy, and age and children do not lead to statistically different responses in either country. We checked whether the marginal utility of income changes with the level of income, and our results are consistent with the expectation that wealthier persons have a smaller marginal utility of income, but this effect is not statistically significant at the conventional levels.

In column (B) of tables 9 and 10, we augment the model with interactions between the risk reductions and risk perceptions. People who believe air pollution is high value risk reductions much more. The effect on the VSL is about €5 million for Italy and €3.5 million in the UK (2010 PPP euro), which is similar to the results in the previous tables. Of the other interactions we entered in model (B), only that with the belief that it is possible for people to personally do something to reduce harm is significant, and only for the UK. In column (C), the positive coefficient on drisk_govt suggests that a higher value for a risk reduction is held by respondents who believe the government is responsible for reducing cancer and heart disease mortality, all else constant.[81]

In tables 11 and 12 we examine whether respondents value risk reductions differently in the housing context depending on recent activity in the housing market and characteristics of their home. In columns (A) and (B) we see that in both

[81] We believe that the included interactions properly account for heterogeneity in respondents' preferences for a risk reduction. For completeness, we also attempted account for potential unobserved heterogeneity by estimating mixed logit specifications (Train, 2009). However, the maximum simulated likelihood routines would not converge. We speculate that this may be due to the fact that we observe few choice occasions per individual, each with only two alternatives.

countries, all else constant, homeowners who moved within the last 7 years are similar to the rest of the homeowners in the sample. As we expected, the results in columns (C) and (D) suggest that respondents who have relatively expensive homes are less sensitive to the increased cost of a new home associated with a risk reduction (although statistically speaking this effect is only marginally significant at best).

We next examine whether there are any systematic differences across cities by interacting the size of the mortality risk reduction with dummy variables for each of the cities from which our sample was drawn. The results are presented in table 13. In columns (A) and (C) we estimate the model that only includes the cost and an interaction term between the risk reduction and a dummy for each city in Italy and the UK, respectively. The inferred city specific VSLs are presented in figure 2.

We can see that for Italy the VSL estimates vary a bit across cities, with the highest VSL of €10.2 million in Florence. We marginally reject the null hypothesis ($p = 0.0778$) that the respondents' marginal utility from a mortality risk reduction (α) is equal across the 8 Italian cities from which our sample was drawn. However, after controlling for socio-economic characteristics and perceptions regarding air quality and health risks, we fail to reject the null that α is statistically different across the cities, as seen in column (B).

In contrast, in the UK we reject the null hypothesis that α is statistically equal across cities, even after controlling for socio-economic characteristics and perceptions (see column D in table 13). As shown in figure (2), among UK homeowners the highest VSL of €2.933 million is held by those residing in London.

One concern with our models is that, while we emphasized in the questionnaire that the respondent should interpret all risk reductions to apply to himself (or herself) only, respondents may have thought otherwise. If they replaced another risk reduction for the one we expressed to them in the housing choice question, then the risk reductions entered in our econometric models are affected by a measurement error. If the measurement error is classical, then our estimate understates the true value of the risk reduction (Morey and Waldman, 1998).

For good measure, we re-estimated the models after restricting attention to those respondents who are homeowners and live by themselves (n=540 in Italy, and n=316 in the UK). There is no question that these respondents are the only beneficiaries of the risk reduction coming from the hypothetical move. The full results are not reported here for the sake of brevity, but the estimates of the VSL based on these groups of respondents are €3.824 million (Italy) and €359,460 (UK). For Italy, this figure is less than the all-sample VSL. For the UK, this figure is not statistically different from zero.

VII. Conclusion

We have conducted a stated preference study asking Italian and British respondents to engage in tradeoffs between mortality risk reductions associated with improved air quality and the cost of housing. Such tradeoffs are often analyzed using hedonic property value models, an attractive revealed preference technique. Despite the obvious advantage of inferring welfare estimates from actual revealed behavior, hedonic property value models in practice are fraught with difficulties. First, hedonic analyses are often susceptible to omitted variable biases. Second, researchers are often forced to assume, without testing, that buyers and sellers in the property market are well aware of the environmental good of interest, and perceive that good using the same measure specified by the researcher in the right-hand-side of the hedonic price equation.

In this study we take an alternative stated preference approach where we ask respondents to choose between hypothetical variants of their home, where the air pollution levels around the home, and hence the mortality risks, as well as the cost of the home, vary. Since this is a hypothetical setting we are able to implement an experimental design that eliminates the potential for unobserved confounding influences. Furthermore, we do not need to assume that respondents are aware of and correctly perceive environmental measures, we *know* they do. Mortality risks are clearly presented to respondents as an attribute of the home, and respondents undergo several probability tutorials before the conjoint choice exercise.

Only a few studies have implemented a stated preference approach in the context of housing in order to estimate the non-market value of environmental amenities (e.g., Earnhart, 2001; 2002) and disamenities (Jenkins-Smith et al., 2002; Chattopadhyay et al., 2005; Simons and Winson-Geideman, 2005; Phaneuf et al., 2010). In all of these earlier studies environmental quality was defined qualitatively, and we believe that it remains unclear how respondents interpret such subjective measures. A unique contribution of our study is that we measure air quality in terms of health risks (e.g., an X in 1,000 reduction in the probability of dying). To our knowledge this is the first stated preference study in the housing context that uses a clearly defined quantitative measure of the environmental good. There have been several stated preference studies that estimate the value of reductions in health risks (e.g., Alberini and Chiabai, 2007a, 2007b; Alberini et al., 2007; Alberini and Ščasný, 2011a; Tsuge et al., 2005), but to our knowledge we are the first to do so in the context of housing.

Our results, at least in Italy, show that people are willing and capable of making tradeoffs between mortality risks associated with air pollution and the cost of their home. Their responses are consistent with the economic paradigm: The marginal utilities of a risk reduction and income were positive and significant, and so the responses pass the "scope" test. In other words, the larger the risk reduction, the more people are willing to pay for it. We did notice large differences in the VSL between homeowners and renters (€5.775 million versus €1.313 million, respectively), a result that might be explained by income and education differences between the two groups, or perhaps by the fact that homeowners expect to stay at the dwelling for a long time.

In the UK, homeowners reported lower VSL figures (around €1.828 million) than their Italy counterparts, and with renters we were unable to estimate a proper VSL. Since the UK respondents are no less wealthy than the Italy sample, we attribute this result to the fact that our British sample is less concerned about air pollution and its effect on their health.

People who perceive air pollution in their city to be more serious of a problem tend to hold a much higher value for a reduction in mortality risk. We also find heterogeneity in homeowners' WTP for a risk reduction based on some socio-economic characteristics, beliefs regarding government responsibility for mortality risk reductions, the value of their home, and at least in the UK, the city in which they live.

One direction for future research is to conduct a similar study where we vary home structure, neighborhood, and environmental and health risk attributes among the alternative housing bundles. Doing so would allow us to re-create choice experiments that are much more similar to the actual choices one has to make when purchasing a home. In this study, due to practical constraints in the implementation of this questionnaire, we only varied two attributes of the housing alternatives: mortality risks from air pollution and price. Drawing attention to an emotionally sensitive attribute such as mortality risks may lead to exaggerated responses, an effect known as "focusing illusion" in the psychology literature (Schkade and Kahneman, 1998). Including other attributes in the housing alternatives may reduce this potential bias.

Ideally this analysis should be repeated using a similar valuation questionnaire in conjunction with a supplemental hedonic property value study. Both hedonic property value and stated preference methods have their strengths and weaknesses.[82] Building on the combined hedonic and stated preference work of Earnhart (2001, 2002), Chattopadhyay et al. (2005), and Phaneuf et al. (2010) may help us better compare the two approaches, and more accurately identify how environmental quality affects home values, and in turn, welfare.

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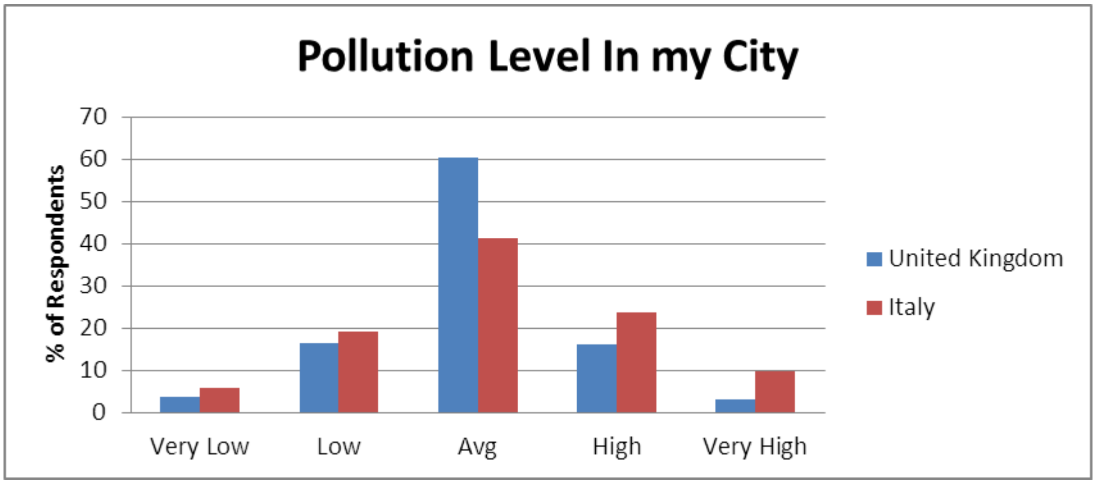
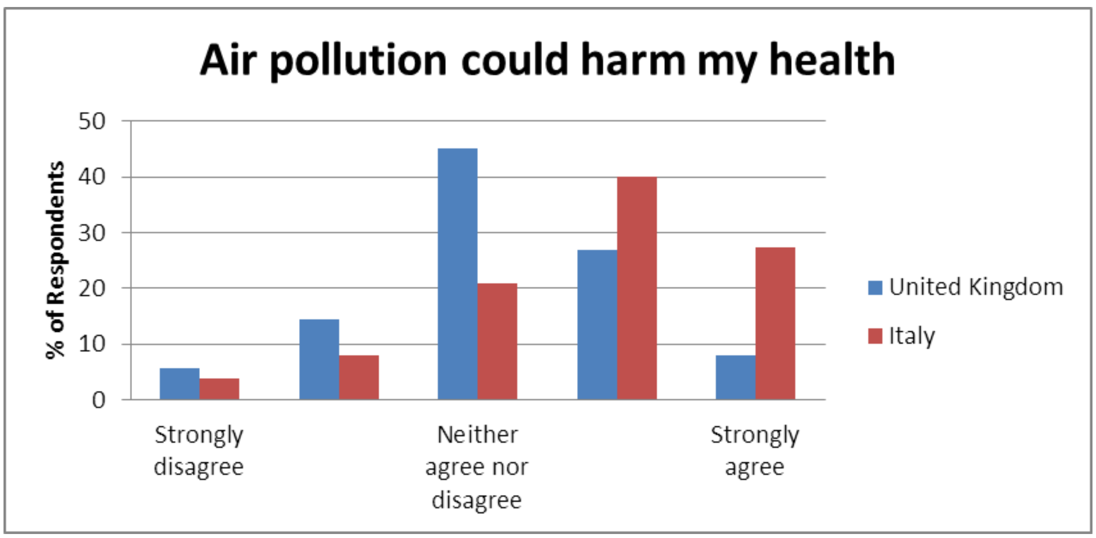
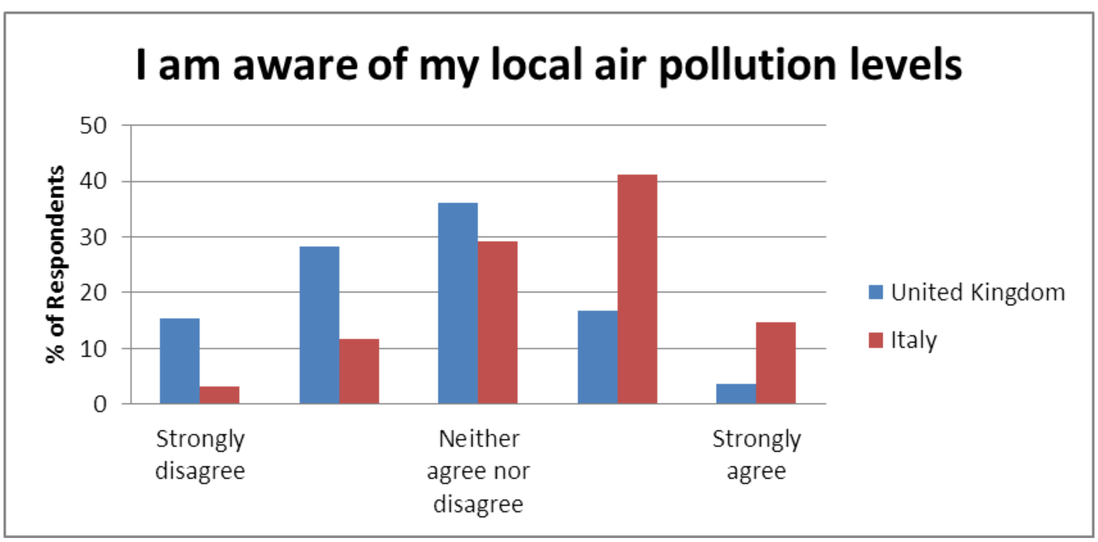
[82] See Whitehead et al. (2008) for a review of studies that combine both revealed and stated preference techniques, the advantages and disadvantages of each method, and how combining these methods can reduce these disadvantages.

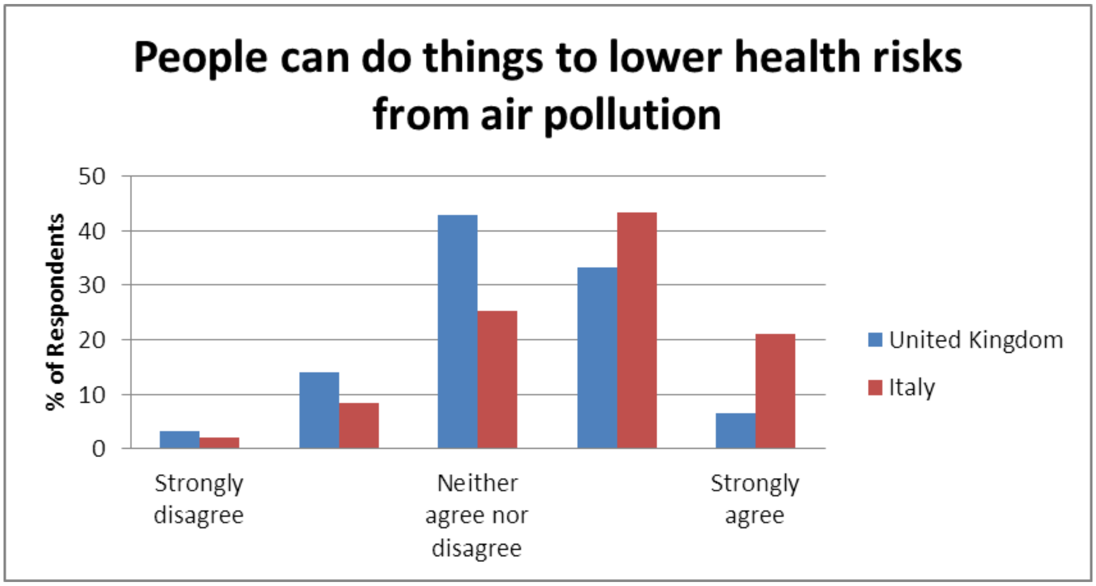
Figures and Tables.

Figure 1. Perceptions of Air Pollution.








People can do things to lower health risks from air pollution
% of Respondents
50
40
30
20
10
0
Strongly disagree
Neither agree nor disagree
Strongly agree
United Kingdom
Italy

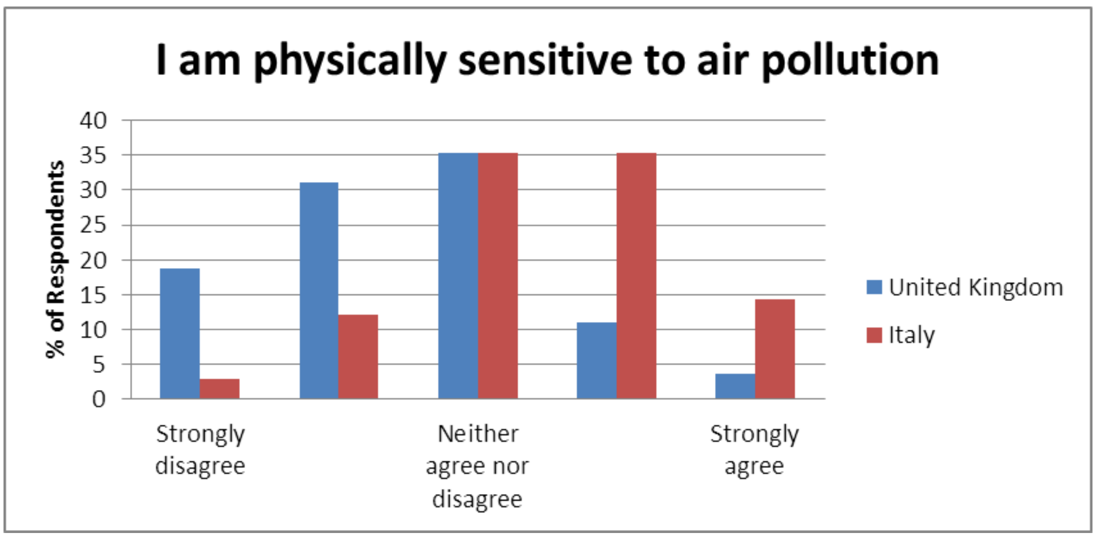
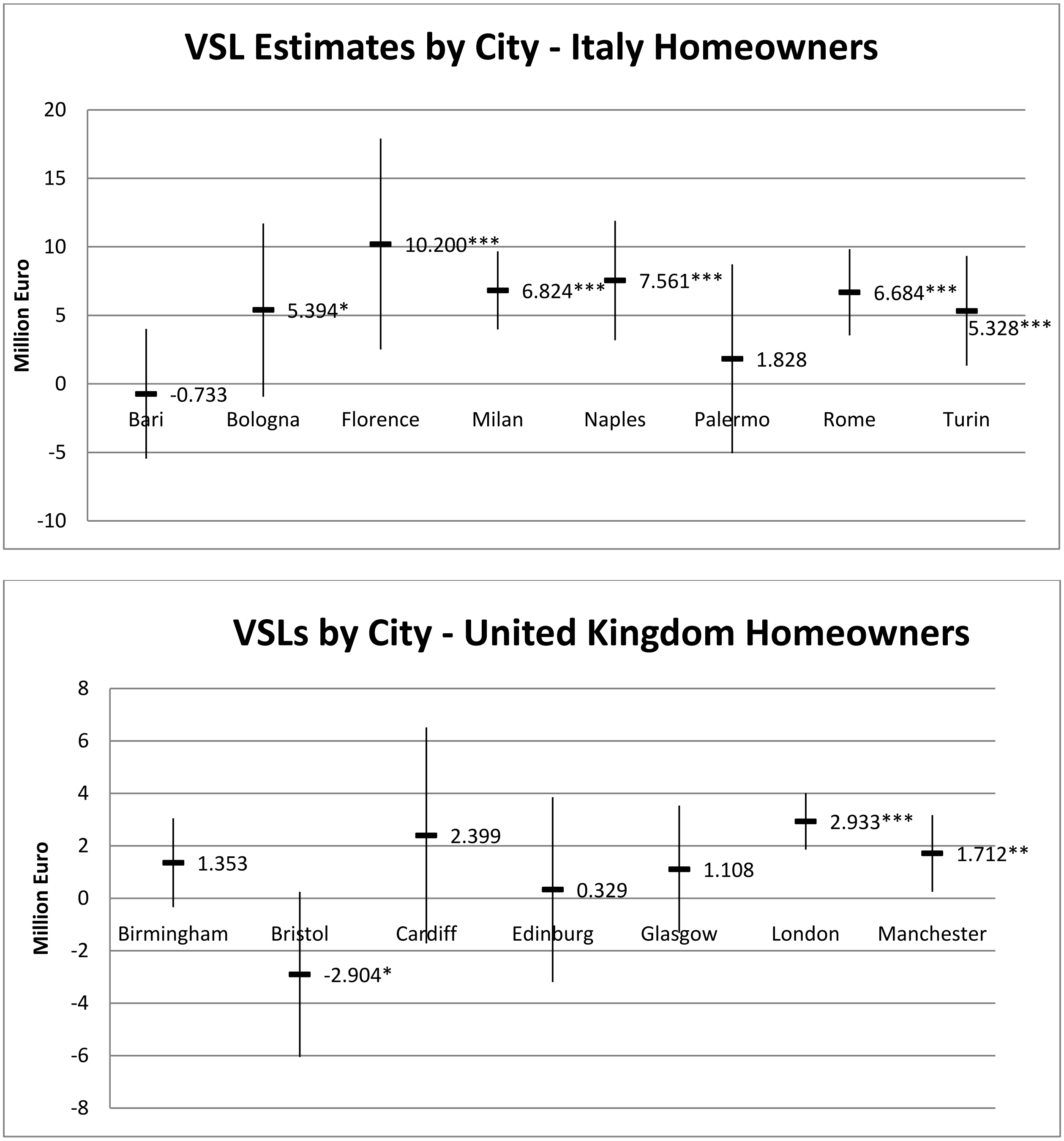

I am physically sensitive to air pollution
% of Respondents
40
35
30
25
20
15
10
5
0
Strongly disagree
Neither agree nor disagree
Strongly agree
United Kingdom
Italy

Figure 2. City Specific VSLs for Homeowners (from models A and C in table 13).



Note: vertical lines denote 95% confidence intervals.

Table 1. Number of Respondents by City.

Italy		United Kingdom	
Bari	236	Birmingham	402
Bologna	130	Bristol	133
Florence	101	Cardiff	58
Milan	629	Edinburg	101
Naples	309	Glasgow	220
Palermo	119	London	982
Rome	513	Manchester	523
Turin	323		

Table 2. Descriptive Statistics of the Sample.

2.a. Italy Respondents

Variable	Obs	Mean	Std. Dev.	Min	Max
Male (dummy)	2360	0.495339	0.500084	0	1
Age (years)	2360	48.73771	5.971482	40	60
Perceived health status (1 to 5, 1=poor and 5= excellent)	2359	3.169987	0.882599	1	5
Married (dummy)	2369	0.747151	0.434737	0	1
Single (dummy)	2369	0.252427	0.434497	0	1
Hhsize (# people in household)	2365	3.1074	1.203267	1	13
has_children (dummy)	2369	0.74293	0.437111	0	1
children0_5 (# of children 0-5 yrs)	1772	0.204571	0.616951	0	13
College degree (dummy)	2369	0.264669	0.44125	0	1
Hhinc (household income, euros)	2368	32391.78	17205.67	0	70001
Owner (dummy indicating home ownership)	2369	0.788518	0.408445	0	1

2.b. United Kingdom Respondents

Variable	Obs	Mean	Std. Dev.	Min	Max
Male (dummy)	2419	0.512195	0.499955	0	1
Age (years)	2417	49.74969	6.10116	40	60
Perceived health status (1 to 5, 1=poor and 5= excellent)	2419	3.147582	1.086863	1	5
Married (dummy)	2426	0.634378	0.481704	0	1
Single (dummy)	2426	0.36521	0.481588	0	1
Hhsize (# people in household)	2409	2.6044	1.265763	1	9
has_children (dummy)	2426	0.666117	0.471696	0	1
children0_5 (# of children 0-5 yrs)	1622	0.1418	0.42543	0	3
College degree (dummy)	2426	0.221764	0.415519	0	1
Hhinc (household income, euros)	2426	39276.75	27242.2	0	128972
Owner (home ownership dummy)	2426	0.690025	0.462578	0	1

Table 3. Comparison between Homeowners and Renters.

3.a. Italy Respondents

	Italian Renters			Italian Owners			
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	t-test
male	499	0.476954	0.49997	1861	0.500269	0.500134	-0.925
age	499	47.86774	5.419226	1861	48.97098	6.091349	-3.9304***
Perceived health status	499	3.068136	0.97528	1860	3.197312	0.854248	-2.6944***
married	501	0.634731	0.481987	1868	0.777302	0.416169	-6.0441***
single	501	0.363274	0.481423	1868	0.222698	0.416169	5.9653***
hhsize	498	2.985944	1.37006	1867	3.139796	1.152962	-2.2983**
has_children	501	0.692615	0.461872	1868	0.756424	0.429355	-2.7862***
children0_5	350	0.235714	0.626089	1422	0.196906	0.614662	1.0426
children0_18	350	1.552857	3.650675	1422	1.085091	2.270997	2.2905**
collegedeg	501	0.211577	0.408835	1868	0.278908	0.448582	-3.2050***
hhinc	500	25750.51	16061.3	1868	34169.42	17070.3	-10.2706***

3.b. United Kingdom Respondents

	UK Renters			UK Homeowners			
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	t-test
male	749	0.46996	0.49943	1670	0.531138	0.499179	-2.7859***
age	749	48.92924	5.867436	1668	50.11811	6.169556	-4.5331***
Perceived health status	749	2.798398	1.151933	1670	3.304192	1.018543	10.3399***
married	752	0.445479	0.497349	1674	0.719235	0.449507	-12.9103***
single	752	0.553192	0.497494	1674	0.280765	0.449507	12.8448***
hhsize	748	2.393048	1.313326	1661	2.699579	1.232367	-5.4017***
has_children	752	0.651596	0.476782	1674	0.67264	0.46939	-1.0103
children0_5	494	0.131579	0.413875	1128	0.146277	0.430497	-0.6502
children0_18	494	1.02834	2.016968	1128	0.912234	1.259678	1.1824
collegedeg	752	0.146277	0.353619	1674	0.255675	0.43637	-6.5374***
hhinc	752	26563.01	20155.21	1674	44988.06	28072.64	-18.3248***

Table 4. Respondents Choosing Home A vs. Home B.

Table 4.a. Percent Respondents Choosing Home A vs. Home B.

Home Choice	Freq.	Percent	Cum.
Question 1			
A	2,618	54.6%	54.6%
B	2,175	45.36%	99.96%
NA	2	0.04%	100%
Total	4,795	100%	
Question 2			
A	2,515	52.45%	52.45%
B	2,278	47.51%	99.96%
NA	2	0.04%	100%
Total	4,795	100%	

Table 4.b. Percent Respondents Choosing Home A vs. Home B by Country.

Home Choice	UK	Italy	Total
Question 1			
A	1,444	1,174	2,618
	(59.52%)	(49.56%)	(54.6%)
B	981	1,194	2,175
	(40.44%)	(50.4%)	(45.36%)
NA	1	1	2
	(0.04%)	(0.04%)	(0.04%)
Total	2,426	2,369	4,795
	(100%)	(100%)	(100%)
Question 2			
A	1,273	1,242	2,515
	(52.47%)	(52.43%)	(52.45%)
B	1,152	1,126	2,278
	(47.49%)	(47.53%)	(47.51%)
NA	1	1	2
	(0.04%)	(0.04%)	(0.04%)
Total	2,426	2,369	4,795
	(100%)	(100%)	(100%)

Table 5. Base Estimation Results: Italy.

VARIABLES	(A) Homeowners	(B) Renters
drisk	0.090107***	0.078374**
	(0.016739)	(0.033405)
dcost	-0.000016***	-0.000060***
	(0.000003)	(0.000007)
VSL	5,774,708***	1,313,378***
	(800,577)	(463,307)
Observations	7,472	2,000
ll	-2576.7344	-629.7753

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 6. Base Estimation Results: United Kingdom.

VARIABLES	(A) Homeowners	(B) Renters
drisk	0.066033***	-0.044138
	(0.018082)	(0.028194)
dcost	-0.000036***	-0.000070***
	(0.000003)	(0.000006)
VSL	1,828,219***	-628,177
	(301,358)	(440,770)
Observations	6,696	3,004
ll	-2244.2098	-837.7145

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 7. Estimation Results with Risk Perceptions of Italy Homeowners.

VARIABLES	(A)	(B)	(C)	(D)	(E)
drisk	0.061870***	0.048012**	0.068020***	0.063965***	0.064588***
	(0.018218)	(0.023179)	(0.020956)	(0.022758)	(0.020028)
drisk_high	0.096836***				
	(0.024970)				
drisk_harm		0.063147***			
		(0.024134)			
drisk_aware			0.039912*		
			(0.022877)		
drisk_lower				0.040011*	
				(0.023668)	
drisk_sensitive					0.052564**
					(0.022786)
dcost	-0.000016***	-0.000016***	-0.000016***	-0.000015***	-0.000016***
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Observations	7,472	7,472	7,472	7,472	7,472
ll	-2569.1384	-2573.3099	-2575.2120	-2575.3058	-2574.0698

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 8. Estimation Results with Risk Perceptions of UK Homeowners.

VARIABLES	(A)	(B)	(C)	(D)	(E)
drisk	0.045574**	0.021117	0.035400*	0.031320	0.057136***
	(0.018771)	(0.019993)	(0.019066)	(0.020322)	(0.018858)
drisk_high	0.141091***				
	(0.034076)				
drisk_harm		0.140175***			
		(0.026122)			
drisk_aware			0.160320***		
			(0.030895)		
drisk_lower				0.094732***	
				(0.025126)	
drisk_sensitive					0.059243*
					(0.035623)
dcost	-0.000036***	-0.000037***	-0.000036***	-0.000037***	-0.000036***
	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000003)
Observations	6,696	6,696	6,696	6,696	6,696
ll	-2235.5555	-2229.7145	-2230.5736	-2237.0838	-2242.8264

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 9. Estimation Results with Socio-demographic Characteristics and Risk Perceptions: Italy Homeowners.

VARIABLES	DESCRIPTION	(A)	(B)	(C)
drisk	mortality risk	0.063561***	0.003768	-0.088958**
		(0.022650)	(0.029201)	(0.036537)
drisk_above55	drisk × (age>55 dummy)	0.011345	0.013201	0.017783
		(0.027786)	(0.027975)	(0.028139)
drisk_college	drisk × college degree dummy	0.079147***	0.072967***	0.066036**
		(0.026257)	(0.026422)	(0.026561)
drisk_male	drisk × male dummy	-0.006627	-0.000877	-0.000699
		(0.023089)	(0.023231)	(0.023344)
drisk_child0_5	drisk × has child 0-5 yrs old (dummy)	0.038496	0.043560	0.047686
		(0.037440)	(0.037619)	(0.037902)
dcost	cost	-0.000017***	-0.000017***	-0.000017***
		(0.000003)	(0.000003)	(0.000003)
dcost_highinc	dcost × (income > national median homeowner income dummy)	0.000005	0.000005	0.000004
		(0.000004)	(0.000004)	(0.000005)
drisk_high	drisk × "air pollution where I live is high" (dummy)		0.086629***	0.080635***
			(0.025407)	(0.025526)
drisk_sensitive	drisk × "I am physically sensitive to air pollution" (dummy)		0.032046	0.018645
			(0.024430)	(0.024735)
drisk_lower	drisk × "people can personally do things to lower their health risks" (dummy)		0.025514	0.008230
			(0.025166)	(0.025627)
drisk_govt	drisk × "government should be responsible for reducing risks" (dummy)			0.135643***
				(0.031495)
Observations		7,444	7,444	7,444
ll		-2560.5571	-2551.6762	-2542.2904

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 10. Estimation Results with Socio-demographic Characteristics and Risk Perceptions: UK Homeowners.

VARIABLES	DESCRIPTION	(A)	(B)	(C)
drisk	mortality risk	0.082791***	0.025792	0.003820
		(0.025214)	(0.027623)	(0.028616)
drisk_above55	drisk × (age>55 dummy)	-0.032104	-0.031603	-0.026711
		(0.027271)	(0.027541)	(0.027644)
drisk_college	drisk × college degree dummy	0.035783	0.026720	0.021447
		(0.028456)	(0.028851)	(0.028992)
drisk_male	drisk × male dummy	-0.041048*	-0.038634	-0.040700
		(0.024717)	(0.024923)	(0.024998)
drisk_child0_5	drisk × has child 0-5 yrs old (dummy)	0.030697	0.030370	0.030720
		(0.045449)	(0.045890)	(0.046026)
dcost	cost	-0.000037***	-0.000037***	-0.000038***
		(0.000004)	(0.000004)	(0.000004)
dcost_highinc	dcost × (income > national median homeowner income dummy)	0.000002	0.000001	0.000002
		(0.000005)	(0.000005)	(0.000005)
drisk_high	drisk × "air pollution where I live is high" (dummy)		0.134617***	0.130066***
			(0.034680)	(0.034813)
drisk_sensitive	drisk × "I am physically sensitive to air pollution" (dummy)		0.026185	0.014079
			(0.036562)	(0.036915)
drisk_lower	drisk × "people can personally do things to lower their health risks" (dummy)		0.094493***	0.086956***
			(0.025564)	(0.025743)
drisk_govt	drisk × "government should be responsible for reducing risks" (dummy)			0.079252***
				(0.026179)
Observations		6,680	6,680	6,680
ll		-2235.3589	-2219.8615	-2215.2805

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 11. Estimation Results with Home Characteristics and Housing Market Experience: Italy Homeowners.

VARIABLES	(A)	(B)	(C)	(D)
drisk	0.090135***	0.003853	0.093974***	0.008352
	(0.016743)	(0.029206)	(0.016901)	(0.029604)
dcost	-0.000016***	-0.000017***	-0.000018***	-0.000018***
	(0.000003)	(0.000004)	(0.000003)	(0.000004)
× moved w/in 7 yrs	-0.000000	-0.000001		
(dummy)	(0.000005)	(0.000005)		
× (home value in top			0.000009*	0.000006
25% of homeowners)			(0.000005)	(0.000005)
drisk_above55		0.012805		0.010138
		(0.028087)		(0.028441)
drisk_college		0.073077***		0.077453***
		(0.026432)		(0.026858)
drisk_male		-0.000878		-0.002563
		(0.023231)		(0.023466)
drisk_child0_5		0.044214		0.045032
		(0.037852)		(0.038134)
dcost_highinc		0.000005		0.000002
		(0.000004)		(0.000005)
drisk_high		0.086547***		0.086557***
		(0.025412)		(0.025698)
drisk_sensitive		0.032054		0.032714
		(0.024430)		(0.024698)
drisk_lower		0.025482		0.024311
		(0.025167)		(0.025490)
Observations	7,472	7,444	7,328	7,300
ll	-2576.7317	-2551.6637	-2524.5711	-2500.3287

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 12. Estimation Results with Home Characteristics and Housing Market Experience: UK Homeowners

VARIABLES	(A)	(B)	(C)	(D)
drisk	0.066048***	0.025819	0.076013***	0.045644
	(0.018082)	(0.027622)	(0.018570)	(0.028521)
dcost	-0.000035***	-0.000036***	-0.000041***	-0.000041***
	(0.000004)	(0.000004)	(0.000004)	(0.000004)
× moved w/in 7 yrs	-0.000002	-0.000003		
(dummy)	(0.000005)	(0.000005)		
× (home value in top			0.000010*	0.000009*
25% of homeowners)			(0.000005)	(0.000006)
drisk_above55		-0.033216		-0.033646
		(0.027670)		(0.028581)
drisk_college		0.027470		0.023741
		(0.028884)		(0.029498)
drisk_male		-0.038550		-0.053458**
		(0.024926)		(0.025607)
drisk_child0_5		0.033900		0.017240
		(0.046285)		(0.046670)
dcost_highinc		0.000001		-0.000000
		(0.000005)		(0.000005)
drisk_high		0.134353***		0.142992***
		(0.034685)		(0.035740)
drisk_sensitive		0.026068		0.017951
		(0.036565)		(0.037766)
drisk_lower		0.094469***		0.093245***
		(0.025566)		(0.026219)
Observations	6,696	6,680	6,384	6,368
ll	-2244.1123	-2219.6775	-2130.4229	-2105.8033

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Table 13. City Specific Effects: Homeowners in Italy and the UK.

	Italy Homeowners			UK Homeowners	
VARIABLES	(A)	(B)	VARIABLES	(C)	(D)
drisk			drisk		
× Bari	-0.011489	-0.082693*	× Birmingham	0.048517	0.023491
	(0.037115)	(0.044901)		(0.032704)	(0.038547)
× Bologna	0.084503	0.000334	× Bristol	-0.104158*	-0.144425**
	(0.052099)	(0.056810)		(0.054375)	(0.059059)
× Florence	0.160286***	0.093375	× Cardiff	0.086050	0.040091
	(0.060420)	(0.064551)		(0.076469)	(0.080035)
× Milan	0.106908***	0.012781	× Edinburgh	0.011817	-0.012960
	(0.024608)	(0.035086)		(0.064682)	(0.068923)
× Naples	0.118462***	0.029542	× Glasgow	0.039735	0.012686
	(0.035692)	(0.043594)		(0.045406)	(0.049711)
× Palermo	0.028646	-0.061765	× London	0.105202***	0.060003*
	(0.056066)	(0.062124)		(0.023570)	(0.032174)
× Rome	0.104725***	0.010726	× Manchester	0.061389**	0.028840
	(0.027425)	(0.036618)		(0.028935)	(0.035925)
× Turin	0.083470**	0.004620			
	(0.033540)	(0.041106)			
dcost	-0.000016***	-0.000017***	dcost	-0.000036***	-0.000037***
	(0.000003)	(0.000003)		(0.000003)	(0.000004)
drisk_above55		0.013516	drisk_above55		-0.034420
		(0.028138)			(0.027706)
drisk_college		0.073332***	drisk_college		0.034458
		(0.026595)			(0.029241)
drisk_male		0.001524	drisk_male		-0.041291*
		(0.023403)			(0.025100)
drisk_child0_5		0.048630	drisk_child0_5		0.036367
		(0.037878)			(0.046269)
dcost_highinc		0.000004	dcost_highinc		0.000001
		(0.000005)			(0.000005)
drisk_high		0.079319***	drisk_high		0.120171***
		(0.025935)			(0.035186)
drisk_sensitive		0.033500	drisk_sensitive		0.023873
		(0.024536)			(0.036748)
drisk_lower		0.027802	drisk_lower		0.095403***
		(0.025330)			(0.025679)
Wald Test: α equal across cities	p = 0.0778	p = 0.1720	Wald Test: α equal across cities	p = 0.0138	p = 0.0373
Observations	7,444	7,444	Observations	6,680	6,680
ll	-2561.0302	-2546.4757	ll	-2230.1911	-2212.8204

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.10

Chapter 5: Conclusion

Hedonic property values models are one of the primary nonmarket valuation tools used by economists. This approach is particularly attractive because welfare estimates are based on observed market behavior. However, in hedonic studies researchers are usually forced to make two necessary, but often untested, assumptions. The first is that all unobserved and potentially confounding influences on house prices have been correctly controlled for, thus eliminating any omitted variable bias. The second assumption is that the measure of environmental quality specified by the researcher is the one that buyers and sellers in the housing market are actually aware of, and care about. If these assumptions are proven invalid, we may in fact be incorrectly inferring welfare effects from changes in property values. I believe stated preference approaches offer an opportunity to test, and in some cases, circumvent these potentially unwarranted assumptions.

In this dissertation I presented a hedonic property value analysis and two stated preference studies examining how environmental pollution affects home values. I paid particular attention to (i) potentially confounding influences on home prices and (ii) how environmental quality is expressed.

The first study (chapter 2) was a hedonic analysis of how home prices are affected by leaking underground storage tanks (LUSTs) and groundwater pollution. I find that the values of homes near a LUST (e.g., within 500 meters) generally do not decrease upon the discovery of a leak, and there is no clear evidence that prices are affected by cleanup and the closure of a leak investigation. These findings persist even after I go to great lengths to control for potentially confounding influences on house prices, such as including neighborhood fixed effects, repeat sales and spatial econometric models, and quasi experimental approaches accounting for the endogeneity of leaks with house prices.

This raises the question of whether home buyers and sellers *are* aware of the contamination and cleanup events in the first place. This suspicion is confirmed by the fact that I did find a significant 9-12% depreciation at homes where the private well was tested by environmental regulators. These households were well-informed, and likely perceived the LUST as a disamenity since they faced actual (or suspected) health risks. I conclude that despite their ubiquity, the presence of LUST sites and the associated risks may not be known to most people.

A disadvantage of hedonics (and revealed preference in general) is that researchers may not always observe the proper counterfactual. For example, the UST program was established in the mid-1980s, and is very proactive in preventing and minimizing damage from LUSTs. Therefore, there are few homes (at least in Maryland) that experience levels of pollution severe enough to capture how the situation might be in the complete absence of the UST program.

With stated preference studies, it is possible to introduce variation in environmental quality at levels that are infrequently (or never) observed in the actual housing market (Earnhart, 2002). This allows researchers to better establish a counterfactual for estimating the welfare effects of an environmental program. Another advantage of stated preference approaches is that researchers can reduce multicollinearity and omitted variable bias because, by design, stated preference data can introduce variation in environmental quality that is uncorrelated with other observed and unobserved variables. Furthermore, the environmental amenity or disamenity of interest is clearly specified to respondents in the valuation scenario, and so we know exactly what the respondents are valuing.

Framing stated preference studies in the context of home values seems like a natural step to facilitate cross-method comparisons. In fact, Earnhart (2001, 2002) and Phaneuf et al. (2010) actually combine stated preference responses with actual transaction data, and jointly estimate preferences. Beyond that, there have only been a few stated preference studies investigating how environmental goods affect home values (Jenkins-Smith et al., 2002; Chattopadhyay et al., 2005; Simons and Winson-Geideman, 2005). In these studies environmental quality was expressed qualitatively, and it remains unclear how people interpret such subjective measures.

In chapters 3 and 4, I experimented with different quantitative, and clearly specified, measures of environmental quality. To my knowledge these are the first stated preference studies in the context of housing to do so. The study in chapter 3 provided respondents with groundwater pollution levels from a local LUST (e.g., X parts-per-billion), and examines how home prices are affected. Corresponding to the hedonic study in chapter 2, this information mimics that sent to households whose private wells were actually tested for LUST contamination by environmental regulators. I find that higher pollution levels and the presence of an exposure pathway do lead to lower home values, which is consistent with expectations from economic theory.

In chapter 4, I presented a stated preference study where respondents were given the objective mortality risks associated with local air pollution (e.g., an X in

1,000 probability of dying), and were asked to choose between hypothetical variants of their home. Consistent with economic theory, I find that respondents prefer a home that is less expensive, and that is associated with lower mortality risks from air pollution. From these responses, I infer a Value of a Statistical Life (VSL) of €1.828 to €5.775 million euro ($2.422 to $7.653 million USD), which is well within the typical VSL range judged acceptable in the risk and safety literature (Viscusi and Aldy, 2003).[83]

Overall, in my hedonic application I find LUSTs generally have little effect on local home values. I believe this is because buyers and sellers (at least in these housing markets and during this period) are typically unaware of the disamenity. I do, however, find a significant depreciation at homes where I know households are well-informed, as well as in the stated preference studies, where respondents are explicitly informed as part of the study design.

While hedonics is a useful non-market valuation tool, we must be cautious in what we infer from changes in property values, and must pay particular attention to what people know about an environmental good, and how they interpret this information. Stated preference methods offer an opportunity to address these concerns, but lack the advantage of being based on actual market behavior. In some applications, pursuing both approaches will help us better characterize how environmental quality affects property values, and ultimately welfare.

[83] Converted to US dollars using 0.75464 exchange rate, which was the average for the year 2010 (http://www.oanda.com/currency/average, accessed May 31, 2011).

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