Fall 2017

The Economic Impacts of Soil Contamination in Wenatchee, WA

Jessica R. Martin
Central Washington University, jessica.rae.martin@gmail.com

THE ECONOMIC IMPACTS OF LEAD ARSENATE

SOIL CONTAMINATION IN

WENATCHEE, WA

A Thesis

Presented to

The Graduate Faculty

Central Washington University

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

Cultural and Environmental Resource Management

---

by

Jessica Rae Martin

November 2017

CENTRAL WASHINGTON UNIVERSITY

Graduate Studies

We hereby approve the thesis of

Jessica Rae Martin

Candidate for the degree of Master of Science

APPROVED FOR THE GRADUATE FACULTY

______________ ____
Dr. Toni Sipic, Committee Chair

______________ ____
Dr. Chad Wassell

______________ ____
Dr. Craig Revels

ABSTRACT

THE ECONOMIC IMPACTS OF LEAD ARSENATE

SOIL CONTAMINATION IN

WENATCHEE, WA

by

Jessica Rae Martin

November 2017

This study determines the economic impacts of soil contamination as a result of historical pesticide use in Wenatchee, WA. A hedonic regression analysis of home values before, during, and after cleanups of six contaminated schoolyards demonstrates the public's willingness to pay for remediated soil as a housing amenity. A qualitative analysis of media coverage of the contamination and cleanups confirms public awareness and categorizes public perception of risk. Results show a significant positive price effect following remediation, and benefit-cost analysis enumerates sizable private and public financial losses incurred as a result of remediation delay.

ACKNOWLEDGMENTS

I would like to thank the Central Washington University School of Graduate Studies and Research for their generous funding of this research. I would also like to thank my committee – Drs. Toni Sipic, Chad Wassell, and Craig Revels, all of Central Washington University – for their guidance and expertise. Finally, I would like to thank Kaleb Javier of the Central Washington University Department of Economics for his invaluable support with data management and code troubleshooting.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF TABLES (CONTINUED)

Table Page

LIST OF FIGURES

CHAPTER 1

IINTRODUCTION

1.1 Overview

Lead poisoning is a global public health crisis; it is also entirely preventable (WHO 2015). It is a cumulative toxicant, especially harmful to children, and can lead to irreversible nerve and neurological damage even at very low levels (WHO 2015; CDC 2016). Epidemiological research continues to identify grave adverse effects at increasingly low concentrations in the blood, and skeletal and dental accumulations of the toxin may continue to leach throughout the body for upwards of a decade after exposure ceases (Needleman et al. 1990; Lanphear et al. 2005; Bellinger 2008; Levin et al. 2008). Thus, it is widely accepted that there is absolutely no safe level of lead exposure (CDC 2016; WHO 2015).

From leaded gas to lead-based paint, the United States has a long history of delayed and inadequate policy responses to environmental lead contamination (Needleman 1991; Rabin 1998; Kovarik 2005). While gasoline and paint have consistently dominated the conversation about lead as a public health risk, soil is increasingly recognized as a critical exposure pathway, and comprehensive consideration of the multitude of potential sources of lead exposure has become properly recognized as crucial to effective policymaking (Levin et al. 2008). Therefore, public health experts, agency officials, and politicians at the highest levels of American public service have asserted that contaminated soil requires imminent, focused attention in order to avoid repeating the policy mistakes of the past (Mielke and Reagan 1988; ASCTF 2003; Beauvais 2016; Clinton 2016).

While historical pollution from the combustion of leaded gas, dust from lead-based paint, and toxic industrial operations are key causes of soil contamination in urban areas, a lesser-known source affects hundreds of thousands of acres of rural land across the country (ASCTF 2003). For the first half of the twentieth century, lead arsenate was the pesticide of choice for pome fruit orchards across the United States (Shepard 1951). The widespread and liberal use of this chemical has resulted in lead and arsenic contamination that persists in the soil under sites that have since been converted to homes, parks, and schools (Peryea 1998; Hood 2006; Schooley 2008). Nearly 200,000 acres of soil in the state of Washington are contaminated with persistent lead and arsenic as a result of ubiquitous statewide use of the pesticide from 1898 to 1948, with more than 30,000 affected acres in Chelan County alone (ECY n.d.).

Given that the hazards of lead exposure are suffered to a much greater extent by young children, in 2002 the Washington State Department of Ecology began testing parks and schools in suspected areas of contamination across the state. The results led to the statewide implementation of cleanups for a limited number of schools and parks. To date, no official evaluation of these cleanups has been undertaken, and tens of thousands of affected acres remain a public health risk while policymakers determine how to proceed in the face of debated risk and divided opinion. After tests yielded levels of lead and arsenic above the state’s acceptable limits for public exposure, six schools in the Wenatchee School District were included in the Department of Ecology’s pilot cleanup response. A variety of remediation tactics were utilized at varying costs in 2006 and 2008 (ECY 2012b). These cleanups were highly publicized, and opinions about their necessity were marked by the same polarity that has plagued American lead policy since the late 1800s (ASCTF 2003; Kling, Collins; and Marquis 2005; Warner 2005). Although it was covered by the Department of Ecology via the state Toxics Cleanup Program, the cost of remediation was a main point of contention throughout public discourse, as was the debated level of risk to public health.

This study contributes to the existing body of research on lead arsenate soil contamination by providing a quantitative assessment of its impacts on property values in Wenatchee, WA. In addition, it serves to qualify public perception of risk in order to better understand how this affects consumer decisions. More specifically, it examines media coverage of environmental hazards and how it informs individual as well as public evaluation of risk. By analyzing the relationship between area home values and their proximities to five of the six contaminated sites before, during, and after remediation, this study enumerates the public's willingness to pay for soil that is free of lead arsenate contamination. The resulting figure will serve to define the economic impacts of lead arsenate soil contamination and abatement in Wenatchee, WA. Additionally, an analysis of local media coverage of the discovery, measurement, and remediation of school contamination serves to establish public awareness as well as to qualify the role of the media in the perception of environmental risk.

This study provides policymakers in Washington with an objective, economic point of reference for decision-making in regards to the evaluation and remediation of soils contaminated by lead arsenate use. As there are nearly 200,000 acres of suspected contamination statewide, and cleanup efforts have been minimal (Schick and Flatt 2015), the need for such policy is clear. The six cleanup sites in Wenatchee have been designated as needing "No Further Action" by the Department of Ecology (2012), but countless contaminated sites remain across the state (Peryea 1998; ECY 2003; Hood 2006). While the existence and scale of contaminated former orchard lands in Washington State are clear, evaluation and remediation have been viewed as prohibitively complex and costly processes (ECY 2003; Hood 2006). Proceedings and recommendations have consistently been hindered by discord and special interests (ECY 2003; Schick and Flatt 2015), clearly marking the need for objective data.

The utility of this data reaches well beyond Washington, as current and former apple-producing states across the country struggle with this same pollution issue, yet they, too, are lacking a quantitative assessment to include in benefit-cost analyses of policy instruments (Schooley et al. 2009). Without such empirical data – for use either as reference or as benefit transfer values – determination of efficient cleanup actions will likely remain complex, arduous, politicized, and ultimately either non-existent or ineffective. Such inaction serves only to unnecessarily prolong public exposure to toxic substances and increase the risk of adverse effects on society at large. By providing policymakers with a quantitative assessment of contamination and cleanup, more efficient action can be taken, and this risk can be reduced.

According to the Natural Resource Conservation Service (NRCS) of the United States Department of Agriculture (2007), more than 10 million acres of cropland and nearly 7 million acres of rangeland were converted and developed between 1982 and 2007, suggesting that the frequency of issues regarding abatement liability for developers and property owners of formerly agricultural lands will only increase, and the determination of efficient actions will be ever more urgent. While simultaneously minimizing risk and conflict by keeping contaminated areas in orchard production has been proposed as a solution to this problem (Peryea 1998), the aforementioned figures from the NRCS indicate that it is not a realistic one. Thus, as development continues to expand to include more of these potentially contaminated sites, the consideration of public and private preferences will be critical to the decision-making process in regards to health risks and abatement actions.

1.2 Area-Wide Soil Contamination of Washington State

By definition, area-wide contamination comprises large geographic areas with widespread, “low-to-moderate” concentrations of toxic material. For arsenic, this designation means concentrations up to 100ppm, while “low-to-moderate” lead contamination includes concentrations from 500ppm-700ppm (ECY n.d.). Area-wide contamination is fundamentally different from most toxic cleanup sites, in that the contamination is not only much more widely dispersed, but also highly variable within the spatial boundaries of any designated area or portion thereof. More commonly, hazardous sites requiring government remediation action - for example, Superfund sites – occupy much smaller areas with consistently higher concentrations of toxic material.

Thus, both remediation strategy and policy are fairly well established and much more broadly applicable. The fact that area-wide contamination frequently occupies tracts of many square miles of land further complicates remediation planning with the introduction of variable land use and the involvement of multiple municipalities and institutions. A given tract of land affected by area-wide contamination may contain residential developments, open land, schools, parks, and commercial properties. The resulting diversity of use scenarios and structural attributes greatly affect levels of public risk, and any remediation strategy must take this variability into consideration (ASCTF 2003).

A significant portion of the state of Washington is designated as area-wide contamination as a result of toxic levels of lead and arsenic in the soil. According to the Department of Ecology, nearly 700,000 acres of Washington soil is contaminated with lead and/or arsenic as a result of historical industrial practices, with three primary sources that vary by geographic region. King, Pierce, Thurston, and Snohomish counties to the west of the Cascade Mountains, along with Stevens County in the northeast corner of the state, exhibit localized, extremely elevated levels of both toxins as a result of past smelter operations (ECY n.d.). The cities of Tacoma, Harbor Island, Everett, Northport, and Trail (British Columbia) were each home to metal smelters during the first quarter of the 20th century, and these facilities emitted highly toxic plumes of aerosol lead and arsenic particulate that spanned up to 1,000 square miles (640,000 acres) as a result of local geographic features and prevailing winds (ECY 2011.) The chief area of focus in places where soil has been affected by smelter pollution is arsenic contamination, with some areas registering levels as high as 3,000ppm. However, the average level recorded at developed properties is around 100ppm (ECY n.d.) The state's Model Toxics Control Act (MTCA) – the key piece of legislation that has informed the policy actions of this study – has set a soil concentration threshold of 20ppm for arsenic in order to protect the public from its known carcinogenic properties (RCW 70.105D.) This threshold constitutes the level of concentration above which the state is required to take action.

As introduced in the Section 1.1, another primary cause of area-wide soil contamination in Washington state is the historical use of arsenical pesticides in orchards, namely the widespread and liberal use of lead arsenate. While orchards could historically be found in nearly every county of the state, the contamination is largely confined to the most productive and sustained operational areas, namely Chelan, Spokane, Yakima, and Okanogan counties (ECY n.d.). Yakima County is suspected to contain nearly 60,000 acres of toxic soil within its boundaries, while Chelan's orchard-related contamination amounts to just over 30,000 acres (ECY 2012.) For reference, these numbers are equal to 1.59% of total land area for Chelan and 2.11% for Yakima.

In contrast to smelter contamination, the chief concern for soils affected by historical orchard practices is toxic lead contamination. The Department of Ecology's testing procedures throughout the counties listed above have recorded lead concentrations as high as 4,000ppm in orchard top soils, with developed properties averaging "generally less than 700ppm" (ECY n.d.). While ambiguous, this figure is still considerably above the MTCA soil concentration threshold of 250ppm for lead.

The third key source of area-wide soil contamination in Washington state is persistent particulate that was regularly dispersed by the combustion of leaded gas before it was banned in the early 1980s. It is suspected that any land adjacent to major roadways that were constructed prior to 1995, as well as soils in densely populated urban areas that experience regularly elevated levels of motorized traffic, have a high likelihood of being contaminated. However, this particular type of contamination has not been prioritized by the state as an area of interest and is therefore not as well understood (ECY n.d.) It has, however become more of a focus in the academic literature as a result of the proliferation of urban agriculture. Researchers are currently seeking to determine if this contamination (along with other common urban soil pollutants) poses a risk to individuals who work to cultivate urban soil as well as those who consume food that was grown in it, but much of this work focuses on former brownfields rather than plots adjacent to roadways (Defoe et al. 2014; Henry et al. 2015).

1.3 The Area-Wide Soil Contamination Task Force: Mission, Issues, Conflicts

Due to the overwhelming complexity of addressing area-wide contamination, the Washington State Departments of Agriculture; Ecology; Health; and Community, Trade, and Economic Development chartered the Area-Wide Soil Contamination Task Force (Task Force) to study the issue in January of 2002. Over the course of 18 months, this diverse group of 17 stakeholders – representing the interests of real estate, education, agriculture, public health, the environment, and economic development – worked to determine a strategy for addressing such contamination and to present a set of recommendations that would streamline the processes required to do so (ASCTF 2003.)

Of chief concern for the Task Force was determining the applicability of the MTCA to area-wide contamination. In addition to the procedural complexity of applying stringent standards to massive areas of land that didn't meet state requirements for public and environmental health, there simply were not the resources to do so. The MCTA (1989) is funded by a state-level hazardous substance tax; revenue is generated by the sale and purchase of petroleum products and pesticides in Washington State. The bulk of the fund is secured by the tax on petroleum products and is therefore subject to the extreme volatility of petroleum markets. So, while the MCTA aims to uphold aggressive standards of public and environmental health in the state of Washington, the fund is unreliable and grossly insufficient to address an issue on the scale of area-wide contamination.

On the west side of the state, a small portion of the financial burden of remediation was alleviated by a legal settlement. As explained in Section 1.2, the primary source of area-wide soil contamination in western Washington is historical smelter operations – the activities of private firms that can be held liable under the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) of 1980. As part of the largest environmental bankruptcy settlement to date, the Environmental Protection Agency (EPA) received nearly $1 billion from the American

Smelting and Refining Company LLC (ASARCO) to clean up areas contaminated by the company's nationwide smelting operations. Nearly $95 million of this settlement went to the Tacoma site (EPA n.d.). While this was not sufficient to fund comprehensive remediation of the affected area, it was enough to address sites of highest priority, like schools and parks, and even to expand into the abatement of residential areas at the epicenter of the plume (ECY n.d.)

However, agricultural firms are frequently not held to the same environmental liability standards as other types of firms, and applying polluter-pays legislation to them is not as straightforward (Tobey and Smets 1996). CERCLA includes an explicit exclusion for pesticides: "No person (including the United States or any State or Indian tribe) may recover under the authority of this section for any response costs or damages resulting from the application of a pesticide product registered under the Federal Insecticide, Fungicide, and Rodenticide Act" [7 U.S.C.A. 136 et seq.] What this means is that no agriculturalist may be held liable for damages incurred by the lawful application of a properly registered pesticide. The drenching of pome fruit orchards in lead arsenate was not only lawful and proper, but it was strongly encouraged by the United States Department of Agriculture in all apple-growing states. It is believed that, were it not, the American apple industry would have been irreparably destroyed by the invasive codling moth (Peryea 1998; Hood 2006). As a result, no current or former orchardist is financially responsible for the remediation of toxic agricultural lands that have since been converted to other uses. So, while the west side of the state has been able to pursue legal action to fund the cleanup of lead- and arsenic-laced soils, the east side has not, largely because it is the result of a protected activity.

The geographic divide in regards to this issue is more than just financial; it is also symbolic of differing values and worldviews that proved to be highly contentious as the Task Force attempted to solve the issue of area-wide soil contamination at the state level. The east-west divide in Washington state is a well-known cultural demarcation that fundamentally stands to represent the classic urban-rural divide, as the western side of the state includes densely populated urban centers like Seattle and Tacoma, plus the state capital of Olympia, and the east is home to more sparsely populated, agricultural communities. It is common in state-level policy conversations for this divide to manifest as eastern residents feeling disenfranchised and/or that their cherished way of life is valued less in the eyes of lawmakers than the livelihoods of those in urban areas, where many more voters live. In regards to the Task Force, the main result of this divide was that the chief representative of the agricultural community refused to sign the final report, and has gone on record multiple times as calling it a waste of resources (ECY 2003; Schick and Flatt 2015.) The pursuit of government-mandated abatement of large swaths of formerly agricultural land was seen not only as a burden on taxpayers but also as an assault on a time-honored livelihood that dominates the eastern Washington landscape.

The second major conflict faced by the Task Force involved the real estate industry. Washington state real estate law mandates that, when the seller of any property is aware of soil contamination, s/he must disclose it to buyers (RCW

64.06.020). So, property owners who have their soil tested and discover it is contaminated can either pay for costly cleanup or suffer a loss in property value – or worse, both (Jenkins-Smith et. al 2002). While it is necessary to avoid a scenario of asymmetric information in contaminated property transactions (Zabel 2007), this particular policy instrument serves primarily to disincentivize testing, because not knowing that a property is contaminated legally releases the owner from the responsibilities of addressing it (Segerson 1994). This absolution via ignorance has the secondary impact of prolonging public exposure to contamination. In addition, even if a property owner solicits testing and does perform appropriate cleanup on any identified contamination, the theorized stigma associated with it is perceived as producing a permanent loss to property value, even though research has demonstrated that this is not necessarily the case (Dale et al. 1999; Boyle 2010; Haninger et al. 2014; Taylor et al. 2016).

Zabel (2007) cites this fear of liability as the main deterrent of development of contaminated properties, but this assumes that the developer is aware of the contamination. In the case of historical orchard sites, this is often not the case. Ignorance of contamination levels is further compounded by an unwillingness to test, due to the abovementioned concerns about risk, liability, and property values. Segerson (1994) cites these liability transfers as negatively effecting willingness to perform environmental assessments. However, she also claims that they positively incentivize investment in abatement by sellers who then capitalize the costs into the price rather than sell at a discount in the face of negative environmental stigma. This indicates that homeowners may be inclined toward significant investment in abatement under the right market conditions and when provided with sufficient information. However, Task Force debates over such potential impacts to property owners escalated to the point that a key stakeholder from the real estate community left the group altogether (Schick and Flatt 2015).

Fundamentally, the work of the Task Force and the subsequent conflicts were centered around the evaluation of risk. The job of the group was to determine where there was sufficient risk to public health to warrant costly cleanup actions. Interestingly, the public health risk of lead exposure was another hotly contested topic of debate. Agricultural and real estate representatives to the group, along with elected officials from the east side of the Cascade Mountains, claimed the risks were being overstated and that cleanup (along with the Task Force itself) was not warranted (Schick and Flatt 2015). While the public health risks of both lead and arsenic are matters of long established medical fact (Rabin 1989; Needleman 1991; Mielke 1998; Abernathy et al. 1999), it was clear to the entire group that there was insufficient epidemiological data to fully understand the precise effects of area-wide contamination in Washington State. The Task Force responded by temporarily halting work in order to issue a preliminary recommendation that the Washington State Department of Health immediately address this critical data gap by drastically increasing blood lead level testing for children across the state (ASCTF 2003). However, the Washington Department of Health does not conduct such testing; it is left entirely to the discretion of individual medical providers. According to the CDC's state-level lead surveillance data, in 2004, one year after the

Task Force issued their final recommendations, less than one percent of Washington children under the age of 6 were tested for lead poisoning (CDC 2016).

After 18 months of contested deliberations and debated recommendations, there were two main outcomes of the Task Force's work. The first was a series of outreach and education efforts to better inform the public about lead risks and exposure prevention. They included suggestions such as removing shoes before entering homes and washing hands after working or playing in soil (ASCTF 2003). The second outcome is the subject of this study: a series of cleanups that focused on schools and parks, because children are known to be at greater risk of suffering the irreversible consequences of lead exposure. In response to the recommendations of the Task Force, the Washington State Department of Ecology funded the remediation of 26 schools and 2 parks in central and eastern Washington, beginning with the Wenatchee School District in the summer of 2006 (ECY 2016).

CHAPTER 2

STUDY AREA

2.1 Census Data

The city of Wenatchee is situated in north-central Washington, approximately 100 miles east of Seattle. It is the largest city in, and county seat of, Chelan County. It covers 7.7 square miles and has a population of 33,636. The median income of the city is $47,168, and 13.7% of residents live below the federal poverty line. There are 13,175 housing units in the city, and the home ownership rate is 56.2%. The median value of owner-occupied housing units is $199,200. Nearly 28% of the population of Chelan County and nearly 18% of the city of Wenatchee identifies as Hispanic or Latino. Both of these numbers are significantly higher than the statewide proportion of 12.4%. Fewer than 83% of residents have a high school diploma, which is significantly lower than the state average of 90.2% Fewer than one quarter of Wenatchee residents have earned a bachelor’s degree or higher (U.S. Census 2015).

2.2 Agriculture

Wenatchee is the self-proclaimed “Apple Capital of the World,” even as tree fruit production in Washington continues to shift south to the Yakima Valley and Columbia Basin. Wenatchee has actively sought to diversify its economic base since the 1990s, but the city moniker represents far more than a mere marketing slogan from the early years of the industry. The history, culture, and aesthetic of orchard operations are ingrained in the psyches and identities of Wenatchee residents (Center for the New West 2000). While the number and size of farms in the area continue to decline (USDA 2012), 7 of the 13 top employers in the City of Wenatchee are still related to the tree fruit industry. Stemilt Growers, the number one tree-fruit producer in the country (Center for the New West 2000), provides more total jobs than any other employer in the city. In all, Wenatchee's tree fruit industry accounts for 57% of total jobs and 38% of full time jobs in the city (Port of Chelan 2015).

According to the United States Department of Agriculture's 2012 agricultural census data, there are 890 farms in Chelan County, totaling 75,820 acres of land. This marks a 9% decrease in the number of farms and a 19.24% decrease in land area used for farming since 2007. Farmland currently accounts for just 4.1% of total acreage in Chelan County (USDA 2012). As the number and size of farms decrease, agricultural land continues to be converted to other uses. It is estimated that 30,463 acres of land in Chelan County (Figure 1) are contaminated by former orchard operations that involved the use of lead arsenate (ECY 2012), and this land has readily been converted to residential developments, commercial areas, parks, and schools (Hood 2006; ECY 2012).

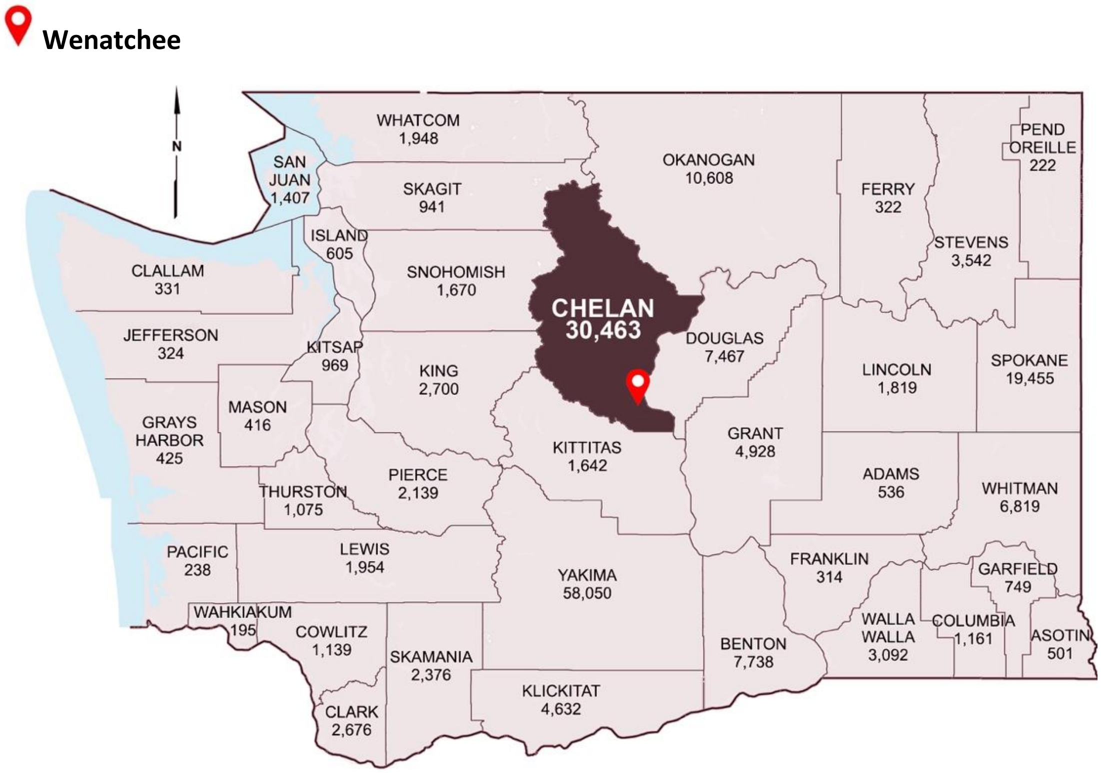


Figure 1. Former orchard land – potentially contaminated acres by county (Adapted from the Washington State Department of Ecology)

2.3 Soil Contamination

Since the regional adoption of orchard irrigation in the early 1900s, orchards in the Wenatchee agricultural region have commonly been planted on soils of the Cashmont and Burch series (Peryea and Creger 1994). These two soil types, along with all soils mapped within the attendance boundaries of schools that underwent remediation, are coarse-loamy, "superactive" soils with a pH range of 7-7.6. The exception is the Wenatchee series, a fine-textured, silty loam that is present in the study area only in relatively low proportions to Cashmont and Burch soils (Soil Survey Staff

2015). While lead and arsenic both form strong bonds to soil particles, each behaves differently in these soils, and the behavior of arsenic is far less predictable and not well characterized overall (Sadiq 1997; Peryea and Creger 1994; Weber and Hendrickson 2006).

Lead forms strong bonds in soil with a high cation exchange capacity, and the "superactive" designation of the soils in the study area indicates that these soils lend themselves to strong adsorption and immobilization of lead (Zimdahl and Skogerboe 1977; Peters and Shem 1992). However, this is not necessarily the case for arsenic, as it responds to different ion types, pH levels, and saturation levels, and its adsorption behavior is unpredictable and often contradictory based on temporal and site-specific soil characteristics (Sadiq 1997). Furthermore, the presence and distribution of each element is further compounded by historical orchard practices like the mixing, transport, and application of lead arsenate along with the tilling, irrigation, and chemical fertilization of orchard soils (Peryea and Creger 1994). However, repeated tests have shown that the study area has consistently high levels of both lead and arsenic at the surface level, and that arsenic shows evidence of considerable leaching downward through the soil solum (Peryea and Creger 1994; Weber and Hendrickson 2006; ECY 2012).

2.4 The Wenatchee School District

The Wenatchee School District (WSD) comprises 12 traditional schools plus a community preschool program, a technical skills center, and an alternative school that serves students in kindergarten through 10th grade. The district serves 7,803 students with 456 classroom teachers and offers a bilingual (English and Spanish) curriculum. 19.7% of its students are English language learners, meaning English is not their native language. Total annual expenditures for the district are $73,961,690 – amounting to a per pupil annual outlay of $9,471 – and it operates on an annual deficit of nearly $1.4 million. Nearly 60% of the districtwide student body qualifies for free or reduced lunch. As Table 1 shows, the school ranks significantly lower than the state average for several key performance indicators, as defined by the Office of the Superintendent of Public Instruction of Washington (OSPI 2016).

Table 1: Key Performance Indicators: State Average (WA) vs. WSD

Indicator	WA	WSD	Difference
Graduation Rate	81.9%	67.9%	-17%
Chronic Absenteeism	15.4%	19.19%	125%
Discipline Rate	3.4%	4.7%	138%

2.5 Cleanup Sites

According to the Department of Ecology (2012), two Wenatchee schools were built on known orchard sites in 1993 and underwent soil remediation during the construction process. Following schoolyard soil testing conducted by Ecology in July of 2002, 4 elementary schools, 1 middle school, and the district high school were put on the state's Hazardous Sites List and marked for remediation. These 6 schools yielded results well above the state's acceptable limits of exposure for lead and/or arsenic, and state-run cleanups ensued in the summers of 2006 and 2008. Table 2 details testing results for all 6 school cleanup sites, and Figure 2 shows their precise locations.

Table 2: Maximum Lead (Pb) and Arsenic(As) Readings in School Soils Requiring Cleanup

School Name	Max Pb	% Above Limit	Max As	%Above Limit
Washington Elem.	1500	500%	317.6	1488%
Lincoln Elem.	1496	498.4%	315	1475%
Sunnyslope Elem.	750	200%	110	450%
Lewis & Clark Elem.	600	140%	100	400%
Orchard Middle	330	32%	90.5	352.5%
Westside High	175	30%	67	235%

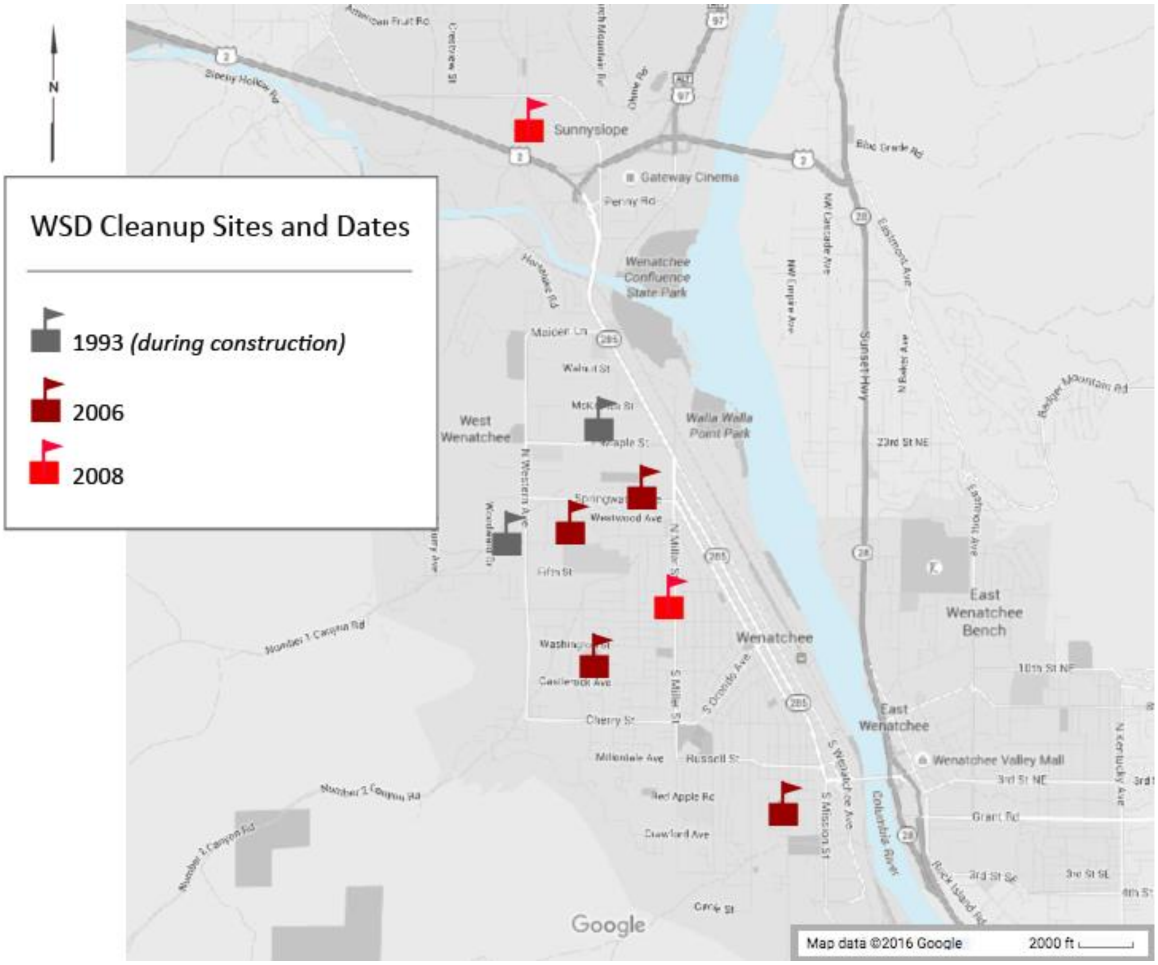


Figure 2. Wenatchee School District cleanup sites (Adapted from Google Maps)

CHAPTER 3

LITERATURE

3.1 Lead Arsenate

From 1898 until the introduction of DDT in 1948, lead arsenate ($PbHAsO_4$) was used extensively across the country as a crucial weapon in orchardists' ongoing battle with *Cydia pomonella*, commonly known as the codling moth (Shepard 1951). It was favored for its affordability, ease of use, persistence, and unmatched effectiveness against this highly destructive pest (Peryea 1998). It was recommended by the USDA and applied to millions of acres of cropland before its ultimate nationwide ban in 1980 (Hood 2006). While lead arsenate was not officially outlawed until 1980, preference for DDT was so strong in Washington State that a universal transition to this new pesticide was essentially instantaneous upon its arrival to the market in 1948 (Peryea 1998).

Lead arsenate was applied as a liquid slurry via handgun sprayers, drenching the foliage, fruit, and ground below. Application rates and concentration levels varied widely depending on species, maturity, and variety of tree as well as pest population size and resistance levels (Peryea 1998). The frequent and liberal application of the chemical rapidly elevated resistance levels in the codling moth, necessitating the switch to DDT prior to the official ban of lead arsenate. In addition, during its 50 years of popularity in Washington State, the progressive frequency of applications at ever-increasing concentrations of the chemical resulted in varying levels of topsoil accumulation of lead and arsenic (Peryea and Creger 1994; Schooley et al. 2008).

Experts and the public raised concerns about arsenic's phytotoxicity and the potential for residual arsenic on mature fruit, but little thought was directed toward soil loading until orchard sites began to be converted to new uses (Peryea 1998; Hood 2006; Schooley et al. 2008). While much is known about the persistence and phytotoxicity of lead arsenate in agricultural soils, questions about public health risks, property values, and options for abatement in the face of land conversion have proven difficult to answer due to asymmetric information, property rights, liability transfers, and agricultural exceptions to polluter-pays legislation (Segerson 1994; Bonnieux et al. 1998; Hood 2006).

3.2 Public Health Risks of Soils Contaminated with Lead and Arsenic

The area-wide contamination that has resulted from lead arsenate use is especially persistent; both toxins experience low mobility in soil (Davenport and Peryea 1991; Weber and Hendirckson 2003). However, arsenic, a well-documented carcinogen (Abernathy et al. 1999), is subject to mobilization under certain conditions that are common to impacted areas. In particular, it has shown to become mobile in the presence of phosphorous in the soil, and phosphorous is frequently applied as an agricultural fertilizer (Davenport and Peryea 1991; Weber and Hendrickson 2003). Despite its high level of adsorption to soil particles, it has also been shown to leach in heavily saturated, alkaline soils, posing the risk of groundwater contamination (Elfving et al. 1994; Peryea and Creger 1994).

Much of the attention directed at arsenic as an environmental health concern has centered around water sources. In the western United States, ground water contamination with inorganic arsenic is typically the result of natural geochemistry, volcanic deposits, and mining activities (Welch et al. 1988). Groundwater contamination poses the risk of well water contamination, and prolonged consumption of arsenic contaminated well water has been linked to increased rates of depression, cancer, diabetes, neuropathy, and cardiovascular disease (Abernathy et al. 1999; Zierold et al. 2004). However, soil is indeed an exposure pathway for arsenic, particularly for children who are more likely to ingest it, either intentionally or incidentally while at play (Abernathy et al. 1999). While the pathway is indisputable, the risk is still unclear; it is determined entirely by the bioavailability of specific, adsorbed mineral species in ingested soil, and this is not readily understood at a site-specific level. The bioavailability of arsenic in soil depends on a wide array of factors such as soil geochemistry, mineral species, and anthropogenic disturbances. There is some evidence that arsenic is less bioavailable in soil than in soluble form; however, in situ experiments are necessary in order to determine the bioavailability of arsenic in soil at each individual contamination site (Ruby et al. 1999).

These same uncertainties surrounding risk arise in regards to lead contamination, as well. The World Health Organization (2015) states: “There is no known level of lead exposure that is considered safe.” Their guidelines, along with the studies cited in Section 1.1, make it clear that even very low levels of blood lead can lead to irreversible neurological damage. Contact with contaminated soil is a significant pathway for human lead exposure, perhaps even more so than contact with lead-based paint, as the toxic material in soil exists in the form of readily inhalable or ingestible dust (Mielke and Reagan 1998). Mielke and Reagan (1998) also assert that only after policymakers acknowledge the public risks of lead in soil can they develop truly effective policies that aim to protect the public from lead exposure. Bowers and Gauthier (1994) point out that the route to the most efficient policymaking should be mapped by epidemiological data, but it is lacking in almost all cases of contamination.

Wolz et al. (2003) examined soil and house dust pathways for homes located on former orchard lands in Chelan County and determined that residences on lots with contaminated soils consistently show elevated levels of lead and arsenic inside the home, as well, demonstrating a clear track-in vehicle for the contaminants in soil particles as well as mobilization and redistribution in the form of dust. However, the key determinant of risk is still bioavailability, which is much less understood than is the fact that humans do indeed inhale and ingest soils contaminated with lead. Once again, situational questions about particle bonds, mineral species, and soil geochemistry must be answered in order to understand the potential health risks of a particular, contaminated site. In addition, gastrointestinal absorption of ingested lead varies widely among individuals and is affected by factors such as age and diet. That said, absorption rates among children have been shown to be between 3.5 and 5.7 times higher than among adults, further underscoring the elevated risk to this segment of the population (Ruby et al. 1999).

The public health implications of soils contaminated by lead arsenate use are complex, uncertain, and the subject of debate (ECY 2003; Wolz et al. 2003; Hood 2006). Despite scientific evidence and the published guidelines of organizations such as the Centers for Disease Control and Prevention and the World Health Organization, the subject of risk has been contentiously disputed throughout the policy development and cleanup process. Hood (2006), along with the Department of Ecology (2003), concluded that the contamination is unlikely to be hazardous, and they propose education and behavioral modifications that minimize exposure pathways as the combined optimal solution. Public opinion in Wenatchee has proven to be polarized. While some have continued to argue that the actual risks to human health are virtually non-existent, and therefore the costs of cleanup unjustifiable (Warner 2005), others contend that, because there is no safe level of exposure to lead, cleanup is socially beneficial at any cost (Kling, Collins, and Marquis 2005).

3.3 Public Perception of Environmental Risks

Risk-aversion is a survival skill. The ability to identify, assess, and avoid danger is critical to any species' genetic perpetuation. The increasingly complex environmental stimuli that inform human perception of risk have elevated it to an academic discipline that saw a surge in the 1970s and has since produced diverse and sometimes conflicting theories on how humans perceive and respond to their environments (Wahlberg and Sjoberg 2000). In his classic work on the subject, Slovic

(1987) asserted that public policy must consider the intricacies and contradictions of this mental process in order to avoid being ineffectual. He also found, as many more have since, that the vast majority of people acquire information about hazards from the media, and thus use media coverage as a basis for evaluating the associated risks.

McCluskey and Rausser (2001) posit that the price effects of environmental hazards are the result of perceived risk rather than actual risk, and follow media coverage in tandem. However, Wakefield and Elliot (2003) observed that people trust their own personal information networks more than traditional news media. They go so far as to claim that personal interaction is the most effective media for risk communication, and that policymakers should consider this in their public information plans rather than relying on conventional outlets. Furthermore, it has been shown that people generally do not fully apprehend quantitative data and thus respond more readily to qualitative and personal assessments (Kohnheim 1988.) The relationships among personal information networks, traditional media, and data reception clearly highlight the challenges of measuring public perception of risk. However, it is still considered a quantifiable entity in the literature (Slovic 1987; McCluskey et al. 2003).

People perceive risk and its proportionally acceptable level of regulation as a tradeoff, essentially weighing risks against benefits of a given technology to determine the publicly demanded level of safety. This process is known as the psychometric paradigm (Starr 1969) and is a commonly utilized theoretical model within the study of risk perception. In the case of this study, the technology is pesticides; the benefit is a profitable apple industry; and the risk is compromised public health. However, the regulatory tradeoff is difficult to elucidate, because people perceive risk to society at large as greater than risk to one's self (Tyler 1988). Thus, public health and personal health are viewed as being under different levels of threat, and many people see their own personal networks of family and friends as being less at risk in the face of hazards than a random, unknown individual in the public at large (Wahlberg and Sjoberg 2000). Interestingly, this behavior contradicts the notion of risk perception as a survival mechanism. Objectively, the perception of greater risk to an individual's genetic material versus to society at large should trigger more protective and/or conservative behavior, thus ensuring future generations. By discounting the risk to self and to family members, the likelihood of prosperous future generations decreases. However, this logic is based on the notion that risk perception automatically influences behavior, and, as Wahlberg and Sjoberg (2000) point out, this has repeatedly been shown to be untrue.

Media coverage of environmental risks in particular has been the subject of numerous studies, and much attention has been directed to why certain risks, like nuclear power, elicit such intensely negative risk responses (Slovic 1987), and why other risks, like lead contamination, have historically received inadequate public attention (Slovic 2000; Brittle and Zint 2003). The general consensus in the literature is that media coverage is event-based and biased toward the sensational. A discussion of risk is generally included in the coverage of sensational events, but it is not normally a part of stories about issues that are not centered around a specific event, like the long-term effects of environmental contamination (Major and Atwood 2004). Furthermore, media coverage of environmental issues is frequently values-based and tends to align with public perception of and/or individual journalists' biases toward a given environmental issue (Wakefield and Elliot 2003; Major and Atwood 2004). This may be reflected in the fact that people believe local newspapers to be consistently biased on these types of issues. However, even this universal notion of media bias is not simple in its application. Wakefield and Elliot's 2003 study of local media coverage of environmental issues showed that the direction of the perceived bias appears to be entirely dependent upon individual views on the subject, so that a single newspaper can be described by its readership as biased in both directions about a single environmental risk issue.

Within the study of media coverage of environmental hazards and their associated risks, lead is frequently treated as a unique issue. Though this may change in coming years in light of the high-profile, events-based coverage of systemic water contamination in Flint, Michigan, the risks associated with lead contamination are not familiar to the average person. In their review of a randomized sample of 152 newspaper articles about lead contamination throughout the country, Brittle and Zint (2003) demonstrated that the media assumes that, because the public knows that lead is a hazard, it is not necessary to explain the risks, so they are not typically included in coverage of lead contamination. This is supported by Slovic's (2000) claim that even though lead is a fairly well known hazard, it is not understood enough to be dreaded. This behavior may be best explained by Tversky and Kahneman's (1973) theory of availability. Their work draws a connection between the level of risk an individual perceives in a given hazard and the availability of an example of someone in her/his personal network who has experienced the negative effects of that hazard. Due to the insidious nature of lead poisoning, a personal example of it is not as “available” to most people as readily as, say, a smoker who succumbed to lung disease. This lack of familiarity has a discounting effect on risk perception. In other words, there is a “bias of imaginability” (Tversky and Kahneman 1973). People do not readily conceive of lead poisoning, and thus it is not feared.

3.4 Costs, Benefits, and Challenges of Soil Remediation

As mentioned in Section 3.3, perceived risks are weighed against perceived benefits in order to arrive at an acceptable level of regulation or a publicly demanded policy instrument. In the case of soil contamination with lead and arsenic, generally low levels of risk perception are weighed against exceptionally costly remediation options. Numerous studies have shown that the high degree of spatial variability of lead arsenate soil contamination poses an array of difficulties for both testing and abatement (Veneman 1983; Peryea and Creger 1994; Hood 2006; McClintock 2012; Defoe et al. 2014). Due to the nature of historical mixing, transport, and application practices, along with the abovementioned immobility of lead and arsenic in soils, an effectively benign sample can be collected mere feet from one of extreme toxicity. Because of this, current testing methods are at considerable risk of underestimating maximum concentrations (Veneman 1983), and vice versa, making an efficient, comprehensive, public cleanup plan exceptionally difficult to develop.

Most remediation methods focus on soil removal or the creation of barriers to interrupt exposure pathways. Excavation, flipping, mixing, and capping are the most common methods for remediating soils contaminated by lead arsenate (Peryea 1998; ECY 2003; Hood 2006). Costs range from $25,000 to $1 million per acre, depending on the extent of contamination and selected remediation method(s), with excavation ranking as both the most effective and the costliest option (Peryea 1998). The broad range of cost and efficacy combined with the innate inconsistencies of testing for these two particular toxins serve to further complicate the evaluation of remediation strategies.

There are public costs to health hazards like lead and arsenic, and those could be lowered by avoidance and/or remediation. By examining the costs of prenatal care and mortality among infants; health care, compensatory education, and lost earning potential among children; and health care, lost wages, and morbidity among adults, Schwarz (1994) enumerated the public costs of generalized chronic lead exposure. His study suggests that a population-wide decrease in blood lead levels of just 1 µg/dL would result in societal savings of $17.2 billion per year, which amounts to $28.5 billion when adjusted for 2017 inflation levels. Such a benefit is sufficient to warrant extensive investment in abatement. In a similar 2009 study, Muennig focused specifically on the social costs of childhood lead exposure with a model that considered lifetime earnings, reduced crime costs, improvements in health, and reduced welfare costs. His calculations showed that reducing childhood blood lead levels by 1ug/dL per child would result in annual savings of $50,000 per child for a total of $1.2 trillion dollars per year, nationwide. In addition to the significant financial benefits, he estimated an additional 4.8 million quality-adjusted life years across the population. And, while her work focused on lead-based paint, Gould (2009) calculated that every dollar of exposure prevention expenditure would yield a return of between $17-$221 in net benefits to society. However, while these numbers support lead abatement at even very high estimates of cost per acre, they do not reconcile the fact that such projects consistently compete for limited resources with more high-profile hazards that are deemed greater and/or more immediate risks (Schick and Flat 2015).

3.5 Economic Impacts of Contaminated Sites on Housing Prices

There are two types of data that can be utilized to estimate the economic impacts of environmental hazards: stated and revealed consumer preferences. Stated preferences are elicited via surveys, and consumers are asked direct questions about their willingness to pay (WTP) for non-tradable goods like environmental quality, and/or their willingness to avoid (WTA) disamenities like environmental contamination. Jenkins-Smith et al. (2002) used a contingent valuation survey to study homebuyers' WTP and WTA for these attributes in an area with contaminated residential soils in Corpus Christi, Texas. Their study showed that when potential homebuyers were given information about disclosure liability, the mere suggestion of contamination risk at a residential property lead 53% of potential buyers to report a WTP of zero for the home. Upon learning that a potential property could possibly be contaminated, and that future disclosure and/or remediation liability would then fall on the owner, more than half of respondents stated that they would simply exit the market altogether.

Li et al. (2015) also utilized contingent valuation surveys in their study of soil and groundwater pollution. Interestingly, they employed the method alongside a hedonic analysis as a means of comparing the two methodologies. They concluded that contingent valuation was a more effective means of determining willingness to pay for environmental quality in a case of soil and groundwater contamination in residential Taoyuan, Taiwan. They cite limitations in available sales data as their main reason for this. In cases where sales data are difficult to obtain, then it is reasonable to assume that contingent valuation may illicit more comprehensive and reliable results. However, it is common knowledge among researchers that survey data and stated preferences are subject to a multitude of biases, because they rely on human responses to human prompts. Thus, it is preferable to acquire the second form of data - revealed preferences - whenever possible. This data are observed in consumer behavior rather than gathered from surveys and questionnaires. Thus, in an ideal quasi-experimental setting, it is subject to significantly less bias. One such method of utilizing revealed preferences to value environmental quality is the hedonic method.

By applying a hedonic price model to real estate values, Rosen (1974) demonstrated that housing prices, like the prices of all tradeable goods, are composite prices of a bundle of characteristics. Housing prices are affected by a variety of structural attributes, such as square footage, room count, fireplaces, pools, etc. They are also affected by neighborhood attributes, such as demographics, school quality, environment, and municipal services. Building on Lancaster's (1966) characteristics approach to consumer theory, Rosen's model (1974) showed that the implicit price of each individual characteristic of a house can be determined by regression analysis. Such an analysis allows for the identification of the price that homebuyers are willing to pay for specific, individual, non-tradeable goods, such as neighborhood services and environmental quality (Palmquist 1988). Thus, while there is no observable market for environmental quality, there is an implicit market for it as a characteristic of a home, and this can be measured. Because of this, the field of environmental economics has come to view hedonic housing price experiments as the optimal approach to evaluating environmental quality, as they utilize observational data to analyze the spatial and temporal impacts of contamination on home prices (Palmquist and Smith 2002).

Many studies have applied this method to air pollution, noise pollution, water quality, and, increasingly, soil contamination (Kohlhase 1991; Thayer et al. 1992; Kiel 1995; Brasington and Hite 2005; Boyle et al. 2010; Mihaescu and von Hofe 2012; Currie et al. 2015; Li et al. 2015; Andersson and Lavaigne 2016). Billings and Schnepel (2017) employed the hedonic method to evaluate the in-home remediation of lead-based paint, largely considered the most significant exposure pathway of lead. Their analysis showed that for every $2 spent on in-home lead-based paint remediation, the home would see an increase in value of $2.60. Most hedonic studies focus on external hazards and use proximity and/or public announcements as proxies for environmental quality. These studies consistently demonstrate a decrease in home values as a result of proximity to contamination (Boyle and Kiel 2001; McCluskey et al. 2003; Mihaescu and von Hofe 2012; Currieet al. 2015; Li et al. 2015; Mastromonaco 2015). Kolhase (1991) found that homebuyers were willing to pay a premium for increased distance from contaminated sites as a result of improved environmental quality and lower risk. However, proximity alone is insufficient as a proxy for environmental quality, and there needs to be a careful evaluation of awareness as part of any valid hedonic housing price study (Guignet 2013).

Many hedonic studies of toxic sites also identify a causal relationship between public dissemination of information and price signals, and they show prices falling and rebounding in direct response to content and timing (Kiel 1995; McCluskey et al. 2003; Boyle 2010). While media may drive the public perception of risk as well as be perceived as biased and/or unreliable (see Section 3.3), it is not the only source of information regarding environmental hazards. Andersson and Lavaine (2016) demonstrated that an official policy to demarcate areas within a French municipality as being vulnerable or not vulnerable to water contamination resulted in a significant drop in home values in the areas deemed vulnerable. This official designation was enough of a signal to trigger a perception of risk great enough for the market to respond. Similarly, agency announcements frequently serve as unbiased, trustworthy, and heavily regulated sources of public information about the entire process of dealing with toxic sites (Kolhase 1991; Kiel 1995). Kolhase (1991) even claims that EPA announcements about environmental contamination create new “safe housing” markets for those who are able to respond to the agency’s information. A failure to group data into time periods based on the dissemination of the various pieces of information released throughout the process of dealing with a toxic site could potentially miss the true source of a price signal (Kiel 1995). In other words, each new piece of procedural information - from initial announcement, throughout cleanup, up until remediation is officially deemed complete - should be utilized as a treatment variable. As will be detailed in Section 4.2, this study employs that method of variable creation.

Boyd et al. (2010) showed that the contamination of school sites in particular triggers a strong negative impact on nearby house prices. They also pointed out that, while private landowners are disincentivized to publicize contamination of their property, thus leading to an asymmetric market, schools must thoroughly publicize such a discovery. As a result, the announcement of school contamination was the driver of both awareness and price effects for their study area. This clearly supports the methodology of this study, which focuses specifically on publicly disseminated information about school contamination as the causal factor of price effects in the study area.

While they are not subject to the same biases and shortcomings as survey data, two of the greatest confounding issues for hedonic studies of toxic sites are omitted variable bias and consumer perception of the hazard. While perception has already been covered extensively in Section 3.3, omitted variable bias is a significant issue that requires intense scrutiny in the pursuit of robust, valid results. If there are unobserved characteristics that are affecting home prices, or if the proxy variables designated to represent environmental quality do not actually reflect what buyers are aware of and/or care about, the results of a study may be invalid (Guignet 2013). In their estimation of a demand curve for environmental quality, Brasington and Hite (2005) determined that homebuyer demand for environmental quality is relatively inelastic (-.12). However, this inelasticity could be due to the highly limited ability to respond to such changes to price. Their estimation of cross-price elasticity shows that school quality and environmental quality are complements, while house size and environmental quality are substitutes. This demonstrates that homebuyers are highly willing to sacrifice environmental quality for a larger home. Households with higher education levels and/or with children exhibit higher levels of demand for environmental quality.

Many hedonic studies of toxic sites address the issue of stigma and attempt to determine whether home values rebound in a community following the remediation of a toxic site (Kolhase 1991; Dale et al. 1999; Boyle 2010; Bartke 2011; Gampar-Rabindran and Timmins 2013; Haninger et al. 2014). It has generally been demonstrated by these studies that home values do rebound. They rebound in response to information, whether it is as a result of media coverage (McCluskey and Rausser 2001) or site-specific, observable information (Boyd et al. 2010). The goal of studying rebound effects is to determine whether remediation is economically efficient, and the overwhelming majority of cases in the literature show that it is. The primary benefit of hedonic housing studies as a means of quantifying the effects of toxic sites and their remediation is the opportunity to inform more efficient policy. Studies that specifically address the rebound effects of remediation actions, such as Leigh and Coffin (2005) and Gamper-Rabindran and Timmins (2013), provide highly practical information for policymakers.

CHAPTER 4

DATA COLLECTION AND VARIABLE CREATION

4.1 Housing Data

The data required for the regression analysis includes housing sales, locations, and structural attributes, along with school district boundary maps, cleanup data, and neighborhood attribute information. Housing data specifically includes detailed information on sales, attributes, and location. All of this is publicly available from the Chelan County Assessor, in the form of sales prices and dates, structural features, and parcel maps. This online database served as the source of all housing data for this study, and the dataset analyzed comprises information about single-family homes sold from 1992 to 2015. The raw sales data was organized and processed according to structural attributes, (age, main area square footage, garage square footage, bedroom count) sale price, and location, in Microsoft Excel. The sales price column header serves as the dependent variable in the regression equation, and the structural and neighborhood features serve as the independent variables. We know that these characteristics significantly affect the price of a home, and, by controlling for them, we aim to enumerate the precise price effect of environmental quality, with remediation process dates serving as the proxy variables. We constrained square footage to a maximum of 3,052 for elementary schools and 3,050 for middle schools (calculated using Q3 + 1.5IQR) in order to remove the effects of outliers. There were no outliers at the low end of square footage, so there was no need to constrain the data to a minimum area. We included a squared covariate of the age term in order to capture the non-linear effects of this variable. In order to control for neighborhood attributes and spatial autocorrelation, which are not specifically detailed in the housing sales data, we utilized publicly available, block-level U.S. Census data (Parmeter and Pope 2009). This is explained further in Chapter 5. Summary statistics for the housing data and treatment variables are listed in tables 3-9.

Table 3. Summary Statistics for all Elementary School Regressions (n=10080)

Variable	Mean	Std. Dev.	Min	Max
Price (in 2015$)	194842.3	125164.1	25195	1600000
Floor Area (in sq.ft)	1504.15	517.7998	276	3051
Bedrooms	2.920833	0.8399458	1	9
Age (in years)	49.8378	30.42196	2	115
Garage Area (in sq.ft)	377.3395	267.6602	0	2304

Table 4. Summary Statistics for All Middle School Regressions (n=9800)

Variable	Mean	Std. Dev.	Min	Max
Price (in 2015$)	194980.3	125493.3	25195	1600000
Floor Area (in sq.ft)	1503.846	517.4219	276	3051
Bedrooms	2.919848	0.8385668	1	9
Age (in years)	49.74962	30.45637	2	115
Garage Area (in sq.ft)	377.2483	267.5311	0	2304

Table 5. Single Family House Prices by School in Wenatchee, WA

School	Count	Mean	Std. Dev.	Min	Max
Elementary					
Columbia	1578	147886.5	52254.48	28470	444468
John Newbury	1912	219436	122201.9	38024	1300000
Lewis and Clark	1218	171460.8	57131.54	25195	536827
Lincoln	1850	189282.4	82978.22	30000	710387
Mission View	533	251683.5	371166.3	41948	1600000
SunnySlope	467	264738.6	134765.7	39020	813830
Washington	2522	195991.8	82674.8	38190	694481
Middle					
Foothills	3317	215046.7	112815.1	38024	1300000
Orchard	3420	175252.1	78773.51	25195	694481
Pioneer	3243	195254.8	167603.9	38190	1600000

Note: All prices in 2015 $.

Table 6. Treated Single Family House Sale Counts for Elementary Schools for Functional Form A Detailed in Section 5.1 (n=10080)

Variables	0-6 mos	0-9 mos	0-1 yr	0-1.5 yrs	0-2 yrs	0-2.5 yrs	0-3 yrs
Announced	203	279	346	518	651	783	897
Listed	201	280	417	587	781	939	1068
Started	224	330	466	664	889	1044	1256
Ended	261	331	459	689	879	1096	1259
Delisted	178	285	338	577	789	1022	1216

Table 7. Treated Single Family House Sale Counts for Middle School for Functional Form A Detailed in Section 5.1 (n=9800)

Variables	0-6 mos	0-9 mos	0-1 yr	0-1.5 yrs	0-2 yrs	0-2.5 yrs	0-3 yrs
Announced	202	277	344	512	643	774	886
Listed	199	275	412	582	775	931	1060
Started	222	328	464	657	882	1036	1247
Ended	257	327	455	681	870	1086	1248
Delisted	177	281	334	571	781	1013	1203

Table 8. Treated Single Family House Sale Counts for Elementary Schools Functional Forms B and C Detailed in Section 5.1 (n=10080)

Variables	0-6 mos	6-9 mos	9-12 mos	1-1.5 yrs	1.5-2 yrs	2-2.5 yrs	2.5-3 yrs
Announced	203	78	65	172	131	132	114
Listed	201	78	135	167	194	158	129
Started	224	106	134	198	224	154	212
Ended	261	70	198	229	190	216	161
Delisted	178	107	160	239	209	233	194

Table 9. Treated Single Family House Sale Counts for Middle School Functional Forms B and C Detailed in Section 5.1 (n=9800)

Variables	0-6 mos	6-9 mos	9-12 mos	1-1.5 yrs	1.5-2 yrs	2-2.5 yrs	2.5-3 yrs
Announced	202	45	65	168	129	131	112
Listed	199	75	135	167	193	156	129
Started	222	106	134	193	224	153	211
Ended	257	70	198	225	189	215	160
Delisted	177	104	157	237	207	232	190

4.2 School Cleanup Data

School data provides two key sets of variables: 1.) a geographic variable to compare with housing data and 2.) the main treatment variables, in the form of cleanup process dates. Rather than utilizing Euclidean distance and buffers, as is common in hedonic housing price models, the nature of this study lends itself to a unique geographic variable in the form of school attendance boundaries. According to Wenatchee School District policy 3130, "students shall attend the school designated for their respective residential area," (WSD 2015). Some amendments have been made to the policy in recent years in order to increase choice with an aim to help alleviate issues of crowding and class size, but these were not in place during the timeframe of this study. So, the vast majority of students attended the schools assigned to their homes, and homebuyers had no reason to believe their own children would not do the same.

Numerous studies have demonstrated a relationship between school quality and housing prices as well as environmental quality and housing prices; in their estimation of a demand curve for environmental quality in housing markets, Brasington and Hite (2005) even demonstrated that it is purchased together with school quality. In addition, Segerson (1994) showed that abatement is an investment, and that sellers of remediated properties capitalize its cost into the price rather than sell at a discount in the face of negative environmental stigma. Thus, it is our assumption that the cost of school cleanups will also be capitalized into the prices of homes that lie within their respective attendance boundaries. This allows us to indicate with a simple yes or no indicator variable whether or not a certain house was sold within the attendance boundary of a contaminated school during treatment/s. Due to the immobility of the contaminants, the hazard is present only onsite. This - combined with the facts that lead has an inordinately negative effect on the health of children in particular, and children are most likely to ingest soil particles through play - reasonably lead to the conclusion that those most at risk are the students at contaminated schools, and this is most effectively captured by attendance boundaries. We obtained school district boundary maps from the Wenatchee School District Office of the Superintendent and digitized them as shapes in ArcGIS for use as an overlay with the parcel maps obtained from the Chelan County Assessor. Using the Intersect tool in Arc GIS, we assigned each housing sale a geographic variable named for the school that would be attended by any children residing in the home. Thus, the treatment group becomes those houses sold within the attendance boundaries of schools that were contaminated and subsequently remediated, and the control group is composed of houses sold within the boundaries of schools that were not contaminated. We confined the data to the city limits of Wenatchee, because countywide data introduced too great a degree of uncontrollable variability, due to the stark socioeconomic and geographic differences between the two areas. The most empirically defensible quasi-experimental model for this research question is derived from city-level sales data segmented by school attendance boundaries.

The second set of school data is the actual contamination and cleanup data. We collected information on the 6 remediation sites from the Washington State Department of Ecology and catalogued it according to location, timing, contamination level, and cleanup type. The 5 key temporal variables for contaminated sites are Announcement, Listing, Cleanup Start, Cleanup End, and Delisting. Table 10 details the timing and duration of the five cleanup treatment variables for each school.

Table 10: Cleanup Treatment Variables

School Name	*Announce*	*List*	*Cleanup Start*	*Cleanup End*	*Delist*
Washington Elem.	11/10/03	8/2/04	7/1/06	9/12/06	12/17/07
Lincoln Elem.	11/10/03	8/2/04	6/10/06	9/1/06	12/17/07
Sunnyslope Elem.	11/10/03	2/7/05	3/29/07	9/30/08	2/12/10
Lewis & Clark Elem.	11/13/03	1/26/06	7/1/06	8/1/06	12/17/07
Orchard Middle	11/13/03	1/26/06	3/29/07	12/31/08	2/12/10

The Announcement variable is the date on which the public was first made officially aware of the contamination. The Department of Ecology sent an "Early Notice" letter to the superintendent of the Wenatchee School District for each of the contaminated schools. The date of the letter serves as the Announcement treatment variable for this study. However, it is not possible to fully measure the level of public awareness that resulted from this letter, and some studies indicate a countervailing effect of such announcement variables, in that the inherent promise of remediation may either trigger a negative price effect in response to fears of a potential hazard, or it may actually increase area property values due to the assumption that cleanup is imminent (Gampar-Rabindran and Timmins 2013). In addition, local media coverage in Wenatchee offered earlier indications than the official letter of a contamination problem at all six schools. Because the date of media coverage is quite likely a better reflection of when the general public initially became aware of the contamination, we created a media variable in order to capture this. This is discussed in Section 4.3. Finally, all "Early Notice" letters were sent in November of 2003, and the first cleanups did not commence until summer of 2006; this lag may have swayed the public's understanding of the severity of the contamination and thus their perceptions of risk. So, the agency-issued announcement is included as a treatment variable, as is standard in the literature, but it is expected to yield ambiguous and/or insignificant price effects for the reasons stated above.

Similarly, the Listing variable is the date on which the Department of Ecology added the site to the state's Hazardous Sites List, but the public effects of a largely procedural milestone with unstated consequences are unclear. Furthermore, the lag between listing and cleanup start is highly variable, with remediation beginning four months after listing for one school and more than two years afterward for several others. This disparity likely served to further confuse the public in regards to the practical meaning of the listing action, and thus hampered their ability to assess its implications for risk. And, Gampar-Rabindran and Timmins (2013) assign the same potential for countervailing effects to the listing variable as they do to the announcement variable. In short, there are several inferences the public can draw from these two variables, and the variable lag time that existed for both announcement and listing in this study may serve to further confound the public.

The cleanup start variable marks the beginning of the onsite remediation process for each school and is thus the first publicly visible indication that a.) the risk is/has been real, and b.) a process is underway to mitigate it. If the public believes that the cleanup will be sufficient to remove the risk from the site, then this should trigger a positive effect. However, if there is especially strong stigma associated with the contamination and its risks, or if there are doubts about the efficacy of the cleanup process, this variable will have no effect. As detailed in Section 3.5, the literature overwhelmingly demonstrates that communities rarely experience permanent stigma from contaminated sites that are sufficiently abated, and that remediation generally triggers positive price effects (or market rebounds in cases where prices have dropped explicitly as a result of the contamination), and that is what we expect from this study, as well.

The cleanup end variable marks the completion of remediation and would thus only underscore those same effects.

While it is part of the same set of agency-issued, mandated communications, the delisting variable differs from announcement and listing in that the implications are unequivocal: the cleanup process is complete, and the site has officially been declared safe by the Department of Ecology. A site is only delisted once it can be assigned a “No Further Action” status from Ecology, meaning cleanup was successful, and contamination levels are below the acceptable thresholds. This is a highly publicized designation. Per the literature, this variable should elicit a positive price response that serves as a rebound to any negative response that occurred earlier in the treatment timeline. A negative response would be highly unexpected in this situation, as it is clear in the literature on risk perception that stigma around lead is low (see Section 3.3). So, barring a complete lack of confidence in the state’s ability to effectively remediate the contamination, the response to delisting should be positive and significant.

Each of the 5 treatment variables is measured at 6, 9, 12, 18, 24, 30, and 36 months from the initial dates (see Table 10) in order to capture any lag in public response. We commenced temporal demarcation of the variables at 6 months prior to sale date in order to account for the nature of the housing market, in which sales transactions are lengthy, and closing procedures average around 3 months. Thus, it is unlikely that there would be significant effects to capture at fewer than 6 months before the final sale date. We included a 9-month iteration in order to better capture the first-year effects, because that is the timeframe during which it is most realistic to assume that buyers will use the information in purchasing decisions. We included models in which temporal ranking was concentric (i.e. 0-6, 6-9, 9-12) as well as inclusive (i.e. 0-6, 0-9, 0-12…) in order to capture the widest variety of temporal effects. We regressed concentric temporal treatments collectively in one regression for each school type (elementary and middle) as well as by treatment type, and then ran inclusive temporal treatments grouped by temporal demarcation. This is explained further in Section 5.1. The creation of a broad temporal range of treatments combined with multiple specifications of each one allows us to capture both short- and long-term price effects and should measure the public's initial response to each treatment as well as identify any long-term impacts that would be attributed to irreconcilable stigma.

4.3 Media Data

Between 2001 and 2010, the *Wenatchee World* printed 40 stories pertaining to the issue of lead arsenate soil contamination in the Wenatchee area. In 2002, the Department of Ecology tested all schoolyards in the Wenatchee School District for contamination. By the end of 2010, remediation of all affected schools had been completed, and all schools in the district were removed from the state's Hazardous Sites List. Thus, this timeframe is inclusive of the discovery of contamination and the start and end dates of all remediation actions. These three events, specific to each school and, thus, also to each home, serve as the basis for the key treatment variables in the regression analysis and are therefore the focus of the media analysis.

The Wenatchee Public Library has a digital archive of all *Wenatchee World* articles, with an unexplained gap in the digital archive from September through December of 2002. I accessed articles from this time period via the microfilm collection at the Wenatchee Public Library. I copied and pasted article content from the digital archives and transcribed articles from the microfilm collection into individual Microsoft Word documents in order to upload them into Atlas.TI, a computer-aided qualitative data analysis program. Table 11 provides an overview of the frequency of articles that mentioned specific schools as being contaminated and were thus utilized to create the media variables for the regression analysis. The media variable is actually a set of three indicator variables that deliver a 1 if there was a newspaper article within 30, 60, or 90 days of the sale date that specifically mentioned the school associated with the attendance boundary of the given home, and a 0 if there was not. This captures the short-term effect of people's perceptions of risk in response to media coverage of a hazard.

Table 11: Frequency of Specific School Mentions in Local News Coverage of Contamination

Year	*Number of mentions*				
	Washington	Sunnyslope	Lincoln	Lewis and Clark	Orchard Middle
2001	2	0	0	0	0
2002	2	4	1	0	0
2003	1	0	1	0	0
2004	1	1	0	1	1
2005	3	0	3	0	0
2006	2	0	3	1	0
2007	1	3	2	2	3
2008	1	3	1	1	3
2009	0	0	0	0	0
2010	0	2	0	0	1
Totals	**13**	**13**	**11**	**5**	**8**

CHAPTER 5

METHODS

5.1 Hedonic Regression Analysis

We merged the housing datasets detailed in Section 4.1 in order to run a fixed effects regression analysis of housing attributes and sale prices using the statistical analysis software program Stata (See Appendix for code.). The fixed effects model controls for time invariant, unobservable attributes in order to avoid omitted variable bias. Based on its predominance in the literature as a means of addressing heteroskedasticity and its ability to control for the wide variation that is inherent to a large set of housing prices (Le Goffe 2000; Boyle 2010; Mihaescu and Hofe 2012), we applied the log-linear form of robust regression in Stata, using the natural log of the sale price as the dependent variable. Robust standard errors enable us to identify unbiased standard errors of the coefficients despite unknown heteroskedasticity in the model. Thus, by applying the log-linear model to ordinary least squares regression, and by reporting robust standard errors, we are able to account for autocorrelation and variable distribution of the error terms themselves. In order to control for spatial auto-correlation, which occurs when the price of a house is dependent upon the prices of houses near it, we included a factor variable of the Census block group number for each house. Similarly, we included a factor variable for time and market factors by concatenating sales year and sales quarter into a single variable called “quarteryear,” to control for housing market variables that are not otherwise captured by the data but vary quarterly. Finally, we clustered the data around school attendance boundaries in order to account for the inherent variability in housing prices across this key geographic indicator for the study. These parameters, along with the robust regression form, impose strict controls on the data in order to yield the most reliable results.

The main equation takes the following conceptual form:

$$\ln(P) = f(H,N,E)$$

where ln(P) is the natural log of the sale (all converted to 2015 dollars using the Western Urban Consumer Price Index from the Bureau of Labor Statistics); H is a vector of house-specific attributes; N is a vector of neighborhood attributes; and E is a proxy for environmental quality. The house-specific attributes are the structural features we obtained from the assessor data. The neighborhood attributes are captured by the Census block group ID variable. The proxy for environmental quality is the set of temporal remediation treatment variables. We grouped the regressions into two main categories: elementary schools and middle schools. While the high school was part of the cleanup program, there is only one high school in Wenatchee, so there is no control group by which to measure its effects; all houses in Wenatchee reside within the attendance boundary of the same high school.

We ran the above described media variables in regressions without the environmental treatment variables in order to avoid conflating effects, as the media frequently provides the first information to the public about a contamination event, and subsequent coverage contains much of the same information as official agency announcements. Thus, the media regression takes the following conceptual form:

$$\ln(P) = f(H,N,M)$$

where H still represents housing attributes, N still represents neighborhood characteristics, and M represents media information. In this case, M is an indicator variable that returns a 1 if there was an article published in the local newspaper that mentions the contamination and/or cleanup of the school associated with a sold house, and a 0 if there was not. The time intervals for the media variable are 0-30, 31-60, and 61-90 days prior to sale date in order to capture the short-term effects of media coverage on purchasing behavior.

For the functional forms detailed below, H, E, and M are carried over from the conceptual forms described above. Thus, β_x represents the set of coefficient estimates for various housing characteristics, namely age, square footage, garage square footage, and number of bedrooms. B_y represents the coefficient estimates of the cleanup treatment variables described in Section 4.2. β_z represents the set of coefficient estimates for the media variables in Form D. For all forms, λ represents the quarterly fixed effect, δ represents N in the form of Census block group fixed effects, and ϵ is the idiosyncratic error term. Subscripts i, j, and t indicate that each variable is affected by individual house, block group, and point in time, respectively.

Form A – Inclusive treatment variables grouped in 6-month intervals
(0-6 months from announce, 0-9 months from announce, … , 0-36 months from announce, all in one regression)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form measures the public's general reaction time by capturing the effect/s of each time interval across treatments, answering the question of which lag (6 months, 9 months, 12 months, … , 36 months) yields the greatest impacts across treatments.

Form B – Concentric treatment variables in a single regression
(0-6 months, 6-9 months, 9-12 months, … , 24-36 months)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

In this form, there is no temporal overlap among treatment variables, and they are all regressed in the same equation. It identifies the impacts of specific temporal ranges, as opposed to the impacts of overall lag as measured in Form A.

Form C – Concentric treatment variables grouped by treatment type
(0-6 months from announce, 6-9 months from announce, … , 30-36 months from announce, all in one regression)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form uses the same concentric interval treatments as B, but they are grouped by treatment type. So, all announcement treatments are regressed together, all listing treatments are regressed together, etc. This form examines the effects of individual treatment types over time.

Form D - Media Treatment Variables Regressed Without Environmental Treatment Variables

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_z \beta_z M_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form captures the effect of media coverage of the contamination on homebuyer's purchasing choices at 0-30, 31-60, and 61-90 days leading up to the sale.

5.2 Computer Aided Qualitative Data Analysis

As is made clear in the literature on risk perception and environmental hazards (see Section 3.3), the public forms a set of beliefs about potential risk as a result of a variety of sources of information, and the role of media coverage is still debated among researchers. After collecting the media data on local newspaper coverage of the contamination and cleanups (see Section 4.3), we performed an in-depth content analysis of the articles in order to qualify the media information that potential homebuyers in Wenatchee were apprehending. Content analysis is one of many ways of analyzing qualitative, textual data; others include ethnography, grounded theory, phenomenology, and historical research (Hsieh and Shannon 2005). The method expands upon more simplistic analytical approaches like word counts and seeks to identify the concepts, ideas, and relationships present within the context of linguistic themes and expressions in order to infer their impacts (Weber 1990). Hsieh and Shannon (2005) define content analysis as "a research method for the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns" (p.1278). Codes are designated thematic concepts that are identified and deemed significant by the researcher, hence the subjective nature of the method. Passages of the text in question are then assigned codes as appropriate, and relationships are identified by semantic associations of cause and effect. Hsieh and Shannon (2005) identify three main types of content analysis: conventional, directive, and summative. We adhered to their above quoted definition of the method and employed the conventional approach as they posit it, avoiding pre-conceived notions of the content and allowing categories and codes to emerge from the data itself rather than from a particular theoretical framework. Figure 3 illustrates the semantic associations among the key codes in the data. Refer to the Appendix for the complete list of codes and their definitions.

We used a computer aided qualitative data analysis (CAQDA) program called Atlas.TI in order to perform this analysis. CAQDA is a methodology that allows researchers to utilize specialized software in order to better identify, organize, and visualize relationships among various codes and categories and to make inferences as to their significance. By conducting a computer-aided media analysis in addition to the regressing the media variable with the housing and cleanup data, we are able to answer two key questions: 1.) Did media coverage of the contamination and cleanups affect consumer decisions? and 2.) Was the coverage sensationalized and/or biased, as much media coverage of environmental hazards has been accused of being? The first question is clearly answered by the coefficient of the media variable in the regression analysis, which was negative and significant, so the answer is yes. The second question is answered by the content analysis, and the answer is no. This is discussed in Section 6.2.

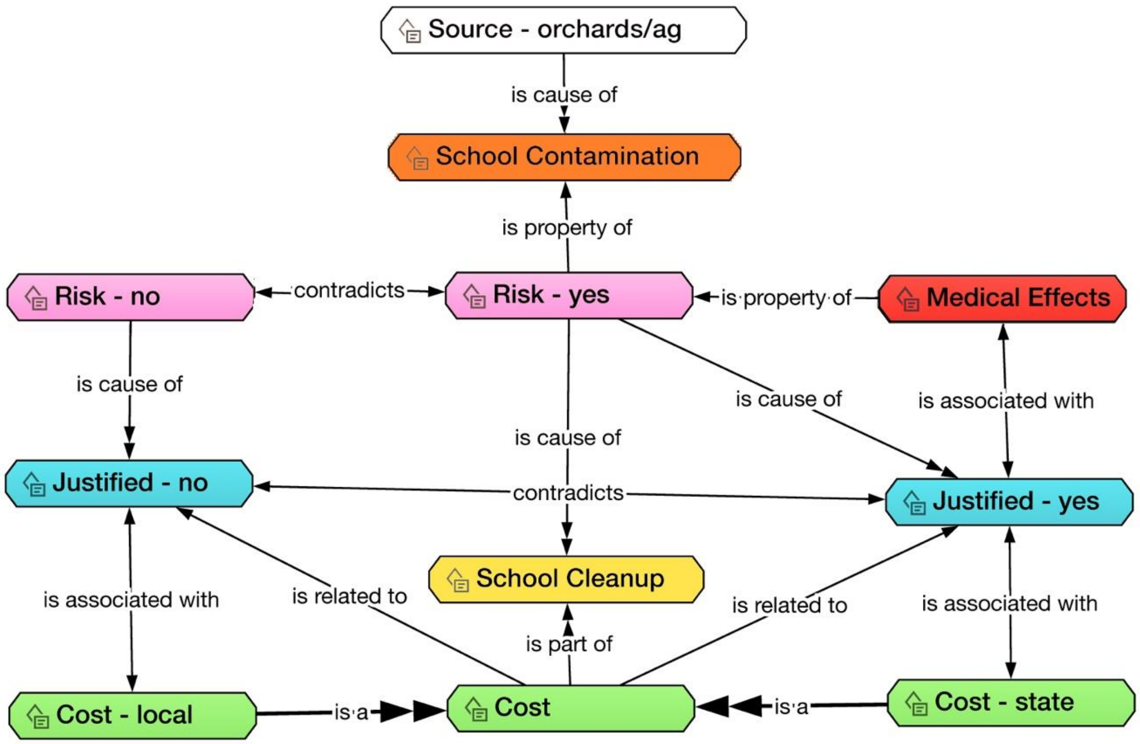


Figure 3. Primary code associations for media coverage of contamination and cleanups

5.3 Benefit-Cost Analysis

We conducted a benefit-cost analysis of a specific level of benefit from the regression analysis in relation to the point in time following cleanup at which it was realized. Thus, the following analysis provides a snapshot of the estimated overall benefits of cleanup. As is clear from the full regression results (See Appendix), there were multiple points during the cleanup process when home values were affected by it, both negatively and positively, so the benefit detailed below is not comprehensive. It represents the estimated benefits accrued during one year in the process following a positive and significant impact from delisting remediated schools. By applying this specific impact from the regression analysis to housing sales data and city property tax rates, and then comparing the results to the costs of cleanup (obtained from the Department of Ecology), we calculated a portion of the benefits and compared them with the total costs of remediating the elementary school soils. The calculations from this analysis are listed in Table 12.

In Table 12, “True Sales” represents the actual sale prices of homes that were a.) sold within the boundaries of remediated schools and b.) sold within 18 months from the delisting date of the associated school. This time period represents one year after 6 months from delisting, when houses sold within the boundaries of remediated elementary schools saw a significant, positive impact across all models. The average impact was a 5.2% increase in value that was attributed solely to the delisting treatment. I used this figure because it is the coefficient that was the most consistent across all models (see Table 15). We assume the price effects of the delisting treatment are impermanent and most likely to be realized for a maximum of 12 months. Thus, affected homes likely saw a 5.2% increase in value for approximately one year after the occurrence of the treatment variable. “True Sales” is the actual sales prices of these homes, so, by removing this 5.2% increase in value from the sales prices of these houses, we calculated “Adjusted Sales.” Thus, “Adjusted Sales” represents the hypothetical lesser value of these homes had the cleanups not occurred and therefore not been capitalized into the prices of these homes. By subtracting “Adjusted Sales” from “True Sales” we calculated the estimated dollar value of the increase in home values that was a result of the cleanups. Assuming that assessor values, on which taxation is based, follow market values, we then calculated “Adjusted Tax” by multiplying the average city property tax rate for this time period (1.33%) to the “Adjusted Sales” figure described above. By subtracting “Adjusted Tax” from “True Tax” (which represents that actual tax collected on these sales), we then calculated the estimated dollar value of tax revenue that would not have been collected had these homes not seen a boost in value from the cleanups. These calculations result in a total “Benefits” figure to compare with the cost numbers obtained from the Department of Ecology. Results of this comparison are detailed in Section 6.3.

Table 12: Elementary School Cleanup Benefits

True Sales	Adjusted Sales	Difference	True Tax	Adjusted Tax	Difference
$96,140,049	$91,140,766	$6,054,922	$1,278,663	$1,212,172	$66,490

Total Benefit = $5,065,773 (sum of differences)

CHAPTER 6

RESULTS

6.1 Hedonic Analysis Results

The results for the elementary school group were unequivocal, with consistent signs (of varying magnitude and significance) across all models. The results show that, even under a variety of model specifications, impacts of treatment variables prior to the start of cleanup were largely negative, and impacts of treatments following the cleanups were largely positive. This is made especially clear by comparing the first treatment, announcement, with the final treatment, delisting. While significance and magnitude varied (see tables 13-19), the signs were consistent with the literature in all functional forms. These findings are explained by the fact that the coefficients of variables like announcement and listing function as signals that a hazard is present, and consumers respond to the risks associated with that hazard. Similarly, variables such as end of cleanup and delisting from the state's Hazardous Sites List marked a collectively perceived end to the risks associated with contamination, and they are in line with the literature on rebounding real estate prices in contaminated and remediated areas. The most consistently significant impacts were those of the delisting treatment variable. At 6 months after delisting, there was a significant, positive impact of approximately 5% in all elementary school models. Elementary school treatment results for Functional Forms A and C are tabled below, and Table 15 illustrates the impacts observed at 6 months from delisting across all functional forms. See Appendix for full regression results.

Table 13. Elementary School Regression Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.042	-0.060	-0.070	-0.095	-0.105	-0.098	-0.098
	(0.060)	(0.068)	(0.056)	(0.054)	(0.058)	(0.055)	(0.062)
Listed	0.011	-0.008	0.077	0.064	0.027	0.012	-0.015
	(0.041)	(0.041)	(0.048)	(0.040)	(0.040)	(0.048)	(0.036)
Started	-0.009	-0.055	-0.056	-0.072	0.025	0.044	0.131*
	(0.097)	(0.054)	(0.074)	(0.058)	(0.048)	(0.052)	(0.063)
Ended	0.052	0.079*	0.053	0.050	0.007	0.007	-0.036
	(0.062)	(0.035)	(0.055)	(0.051)	(0.056)	(0.085)	(0.099)
Delisted	0.054**	0.047**	0.031	-0.072	-0.038	-0.052	-0.065
	(0.020)	(0.019)	(0.026)	(0.122)	(0.103)	(0.092)	(0.025)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.309	0.310	0.310	0.310	0.310	0.311

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

Table 14. Elementary School Regression Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.045	0.016	0.015	0.015	0.052**
	(0.059)	(0.034)	(0.075)	(0.075)	(0.018)
6-9 months	-0.040	-0.029	-0.067	-0.067	0.078
	(0.063)	(0.059)	(0.053)	(0.053)	(0.090)
9-12 months	-0.080	0.179	0.004	0.004	-0.052
	(0.076)	(0.153)	(0.049)	(0.049)	(0.081)
1-1.5 years	-0.130*	-0.021	0.007	0.007	-0.177
	(0.058)	(0.029)	(0.036)	(0.036)	(0.236)
1.5-2 years	-0.135*	-0.068	0.156*	0.156*	0.029
	(0.059)	(0.044)	(0.067)	(0.067)	(0.064)
2-2.5 years	-0.078	-0.081	0.035	0.035	-0.056
	(0.064)	(0.061)	(0.088)	(0.088)	(0.042)
2.5-3 years	-0.051	-0.033	0.161	0.161	0.002
	(0.080)	(0.047)	(0.103)	(0.103)	(0.031)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.311	0.311	0.309	0.310

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

Table 15: Impact of Delisting for Elementary School Regressions

	Form A	Form B	Form C
Impact 6 months after delisting date	.0539**	.0491**	.0521**
	(0.0198)	(0.0169)	(0.0183)

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

The impacts of the delisting are further illustrated in the following impulse response plot of Functional Form B. Figure 4 illustrates the increasingly negative response to the announcement treatment for the first 12 months. Beyond 12 months, there is no clear trend in purchasing behavior as a response to the announcement treatment, and this is to be expected, as the lag is too great to reasonably expect consumers to be reacting to treatment information for that long. Similarly, Figure 5 illustrates the opposite impacts of the delisting treatment, which is positive at the 6 and 9 month marks, but then varied and insignificant as lag from treatment becomes too great to elicit a purchasing response. These plots clearly show that consumers in the Wenatchee housing market had a negative, significant response to the announcement that schools in the district were contaminated, followed by a positive, significant response to schools being delisted from the state’s Hazardous Sites List. Both sets of impacts were temporary.

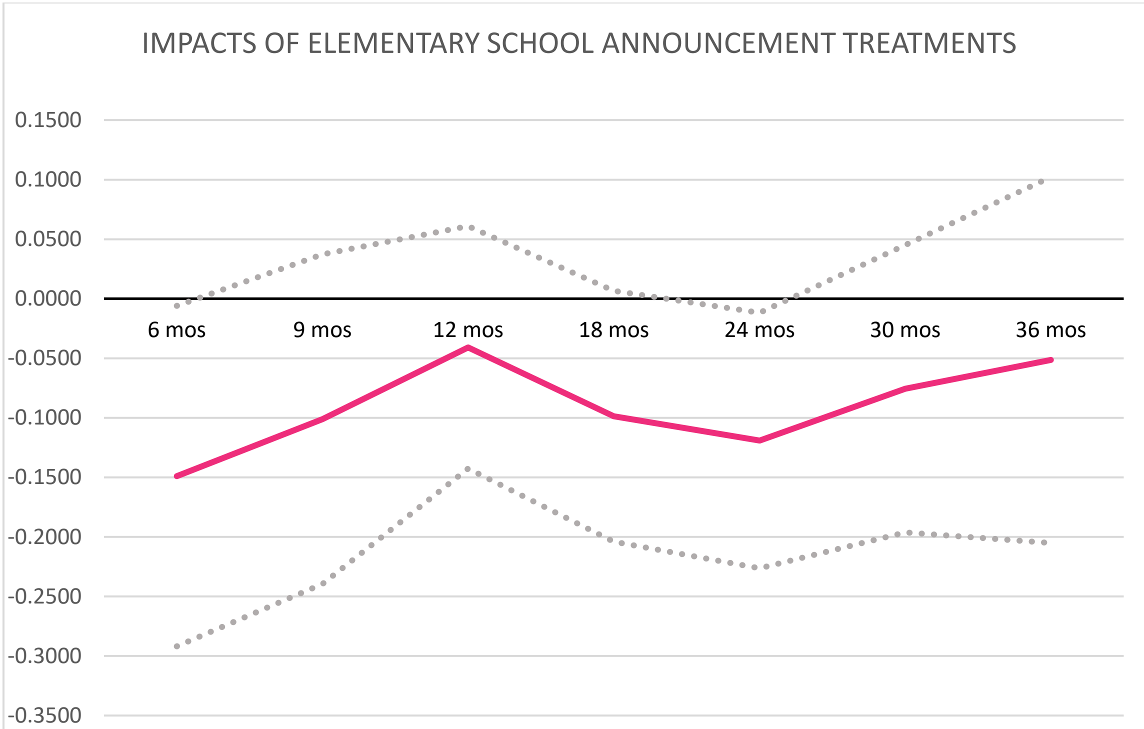


Figure 4. Impulse response plot of elementary school announcement treatments with 95% confidence intervals

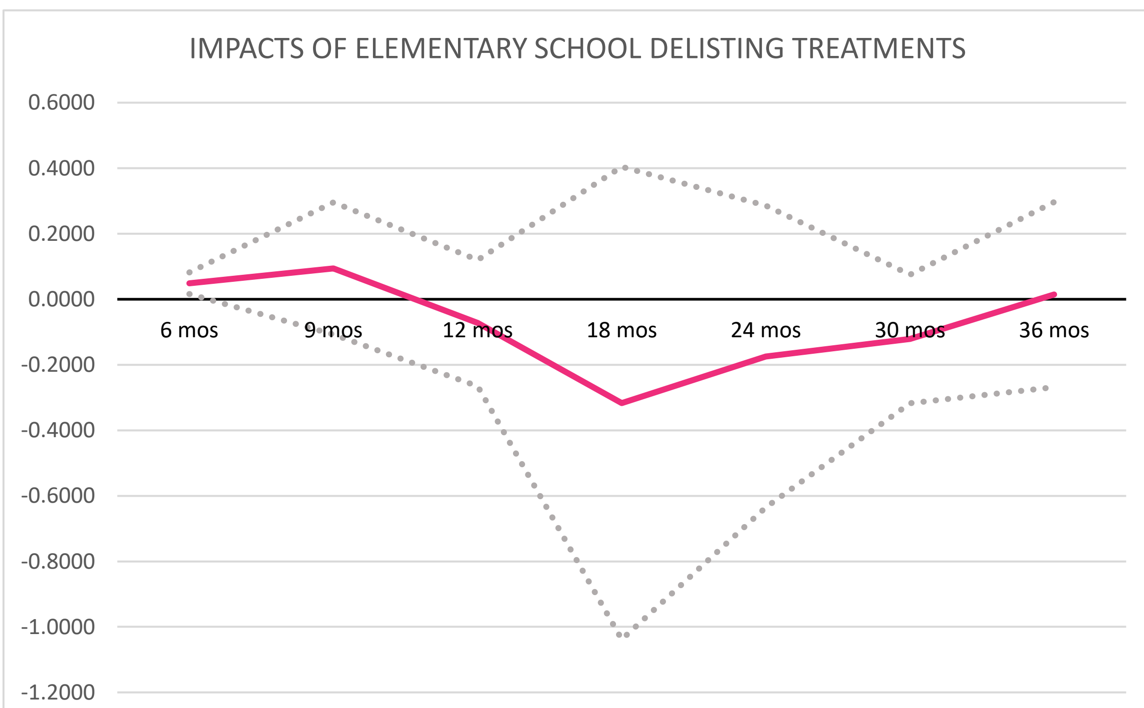


Figure 5. Impulse response plot of elementary school delisting treatments with 95% confidence intervals

Even though they show similar trends for the first year following announcement and the first 9 months following delisting, the results from the middle school regression were slightly more ambiguous. Overall, impacts were less consistent within treatment types and across models. While the announcement and delisting variables generally yielded negative impacts, the end of cleanup yielded positive and negative impacts of varying magnitudes at different temporal markers. However, overall the pre-cleanup treatments produced negative impacts, and the post-cleanup treatments yielded positive impacts. None of the treatments were significant in Functional Form A, but Forms B and C produced significant impacts that follow the trend outlined above.

Table 16. Middle School Regression Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.035	-0.094	-0.073	-0.071	-0.087	-0.078	-0.082
	(0.052)	(0.058)	(0.064)	(0.078)	(0.079)	(0.078)	(0.074)
Listed	0.025	0.003	-0.011	0.017	-0.018	-0.003	0.010
	(0.031)	(0.032)	(0.024)	(0.013)	(0.019)	(0.016)	(0.012)
Started	-0.290	-0.162	-0.107	-0.070	-0.049	-0.028	-0.064
	(0.265)	(0.127)	(0.095)	(0.057)	(0.039)	(0.028)	(0.022)
Ended	0.080	0.125	0.061	0.060	0.049	-0.040	-0.011
	(0.082)	(0.097)	(0.083)	(0.036)	(0.028)	(0.042)	(0.051)
Delisted	-0.009	0.008	-0.004	0.021	0.014	0.039	0.043
	(0.017)	(0.008)	(0.021)	(0.022)	(0.047)	(0.072)	(0.073)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980	9,980	9,980
R-squared	0.311	0.310	0.310	0.310	0.310	0.310	0.310

Note: Robust standard errors in parentheses, clustered on middle school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

Table 17. Middle School Regression Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.050	0.022	-0.292	0.084	-0.004
	(0.065)	(0.034)	(0.27)	(0.082)	(0.012)
6-9 months	-0.209*	-0.035	-0.006	0.187	0.053
	(0.069)	(0.029)	(0.047)	(0.120)	(0.033)
9-12 months	-0.007	-0.046**	0.017	-0.133	-0.024
	(0.102)	(0.007)	(0.032)	(0.049)	(0.065)
1-1.5 years	-0.073	0.018	0.018	0.068*	0.122
	(0.113)	(0.062)	(0.032)	(0.019)	(0.057)
1.5-2 years	-0.141	-0.159**	-0.002	0.014	0.0503
	(0.076)	(0.017)	(0.026)	(0.025)	(0.112)
2-2.5 years	-0.043	0.015	0.027	-0.217	-0.015
	(0.086)	(0.051)	(0.044)	(0.157)	(0.023)
2.5-3 years	-0.073	-0.166*	-0.156*	0.038	0.069**
	(0.053)	(0.055)	(0.044)	(0.032)	(0.014)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980
R-squared	0.310	0.310	0.312	0.311	0.309

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

Table 18: Impact of delisting for all middle school regressions

	Form A	Form B	Form C
Impact 6 months after delisting date	-0.00946	-0.0119	-.00387
	(0.0168)	(0.0149)	(0.0116)

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

Similarly, the impulse response plots for the middle school regression results (Form B) show the same trends as the elementary data displayed figures 4 and 5. The announcement treatment elicits a negative response for the first year, and the delisting treatment elicits a positive one. Beyond the first year, the lag is too great to yield significant results or an identifiable trend in purchasing behavior.

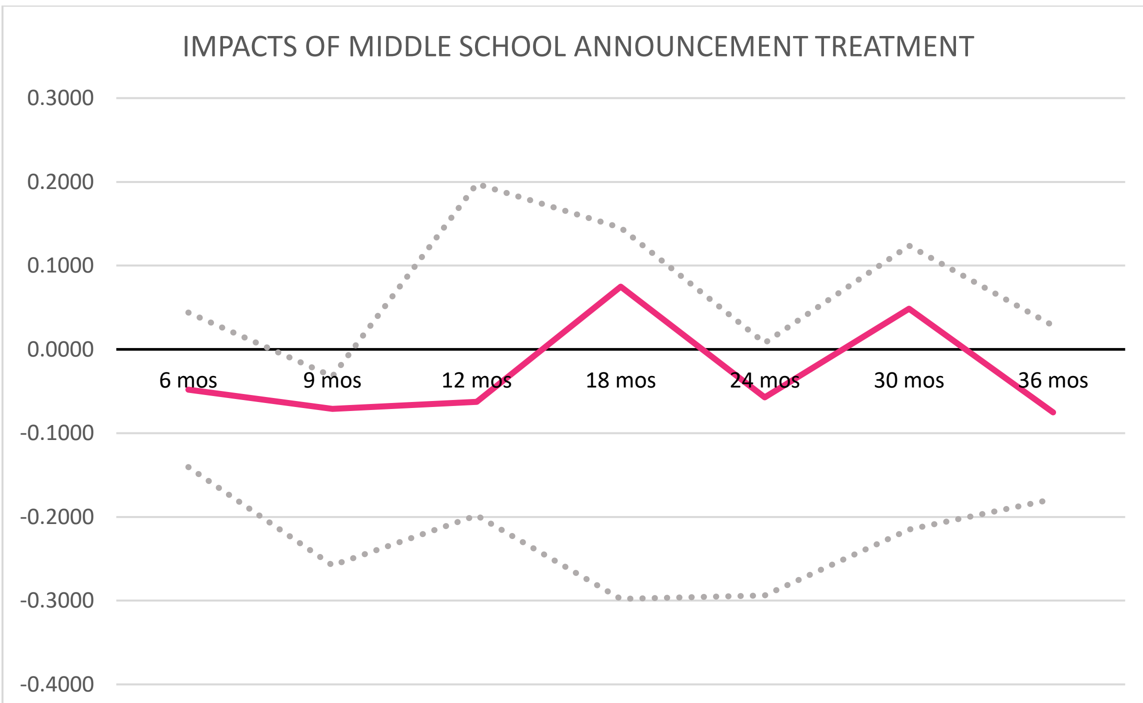


Figure 6. Impulse response plot of middle school announcement treatments with 95% confidence intervals

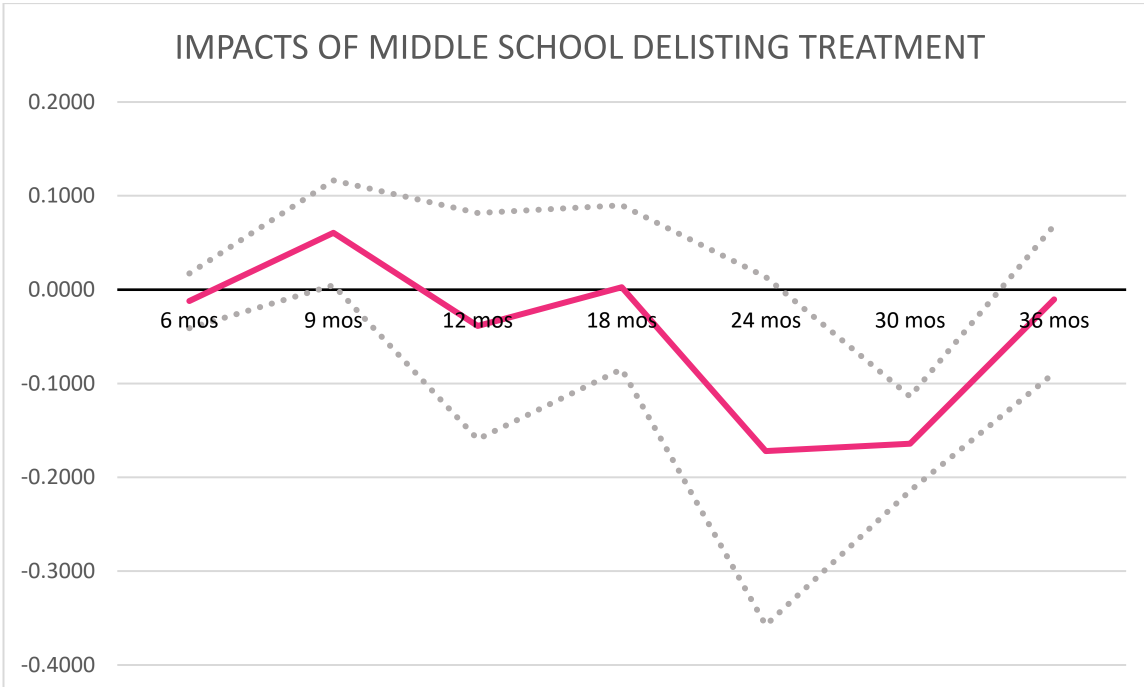


Figure 7. Impulse response plot of middle school delisting treatments with 95% confidence intervals

There are three middle schools in the Wenatchee School District, and only one was treated. This marks the key difference in the data between the middle and elementary school groups. There are seven elementary schools in the district, and four were treated. Thus, the elementary school effects were aggregated from home sales across four different attendance boundaries and over a period from 2004 to 2013, resulting in a higher quality sample with greater exogeneity. The middle school group includes only one treated school, and the treatment spans from 2006 to 2013, with an inordinate lag between treatment variables. In particular, the cleanup period for Orchard Middle School lasted from March 29, 2007 until December 31, 2008, amounting to a 16-month lag between cleanup start and cleanup end. With the exception of Sunnyslope, elementary school cleanup periods lasted just 1-3 months. It is possible that this long period of abatement action is indicative of an especially complicated and/or unsuccessful cleanup, and this could explain negative price impacts associated with its ending. If the cleanup of this particular school was not well understood, or if the public believed it to be unsuccessful, then the completion of the process could very well trigger a negative price effect. However, there is no empirical evidence for or against this claim in either the cleanup or the media data. Thus, we conclude that the incongruous effects of the middle school cleanup are attributed to the fact that there was only one school in the treatment group, and the extreme lag between treatment variables renders it ambiguous.

As illustrated by Functional Form D in Section 5.1, we regressed the three media variables separately from the environmental treatment variables to avoid capturing conflating effects. This equation shows clearly that the media coverage of the school cleanups in Wenatchee did in fact have an impact on purchasing decisions. At each time interval, there was a negative impact to home prices, with the most significant results measured at 31-60 days from sale date. Homes associated with schools that were mentioned by name in a contamination article between 30 and 60 days prior to sale saw a statistically significant decrease in sale price of more than 9%. Results are detailed in Table 19 and are in line with results from the environmental treatment variables as well – there are clear negative impacts to house prices during the announcement, listing, and pre-cleanup phase. When people become aware of the hazard, they are able to respond in their purchasing behavior. This is also consistent with the literature. Even though the presence of lead and arsenic in north central Washington soils was considered a fairly well-known reality (Steigmeyer 2001), the dissemination of official information, whether by agency or media, still served to elicit novel responses from homebuyers. However, the 9.33% negative impact from media coverage is much greater than any statistically significant impact from the official agency announcements. This indicates that the public is influenced more by the local newspaper than by the Department of Ecology.

Table 19: Media Regression Results (n=11,681)

Days between article publication and sale date	Coefficient
0-30	-0.0512
	(0.0358)
31-60	-0.0933**
	(0.0284)
61-90	-0.0321
	(0.0554)
Constant	10.67***
	(0.0534)
R-squared	0.292

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

6.2 Media Analysis Results

The media analysis showed that, by and large, local newspaper coverage of the contamination and cleanups was objective and focused on three key practicalities: the cost of remediation (borne by either WSD or the Department of Ecology), the public health risks (of debated severity), and the source of the contamination (orchards). The software allows for the identification of code co-occurrences, so that researchers can determine the relationships between pairs of key themes. The co-occurrence of codes in the *Wenatchee World* coverage of the contamination and cleanup revealed strong relationships between the themes of cost and liability, expert opinion and the presence of risk, and expert opinion and the source of contamination.

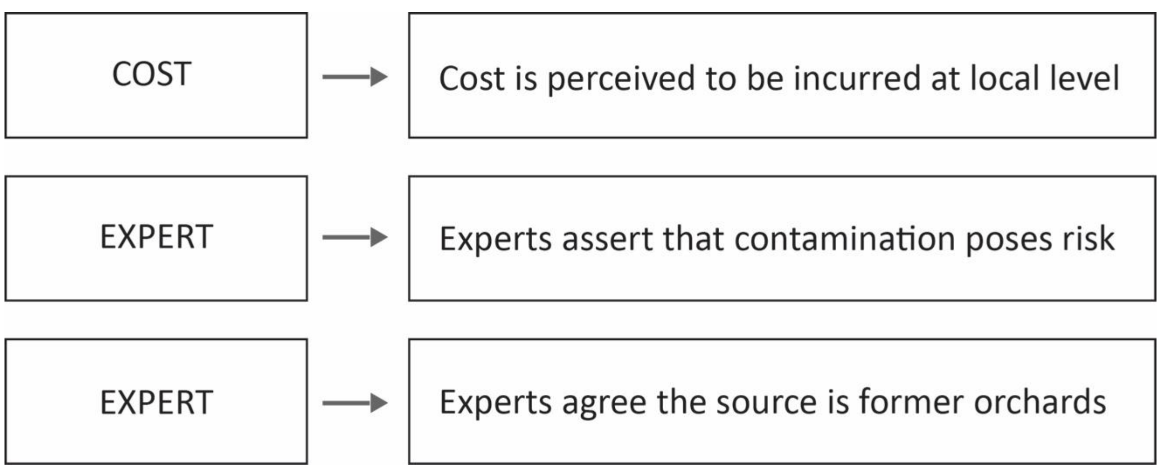


Figure 8. Top three code co-occurrence themes

These relationships are easily explained by objective factors and are in line with the key themes described above. The question of cost was frequently discussed in terms of liability, because the costs were great, and there was a concern that they would be incurred at the local level, by the school district, rather than by the Department of Ecology. The risks associated with the contamination, along with the source of the contamination, were both frequently included in the form of direct quotes from expert sources and official statements by government agencies rather than public opinions and anecdotal claims. While the level of risk was never clearly identified in the media, nor was it possible for it to have been, the fact that it was frequently described and discussed by public health and environmental experts resulted in a fairly measured debate. This is likely one of the key reasons that the *Wenatchee World* coverage proved to be more objective than the literature suggests is typical for such events. Figure 9 enumerates the number of articles that portrayed the cleanup process as positive, negative, neutral, or divided.

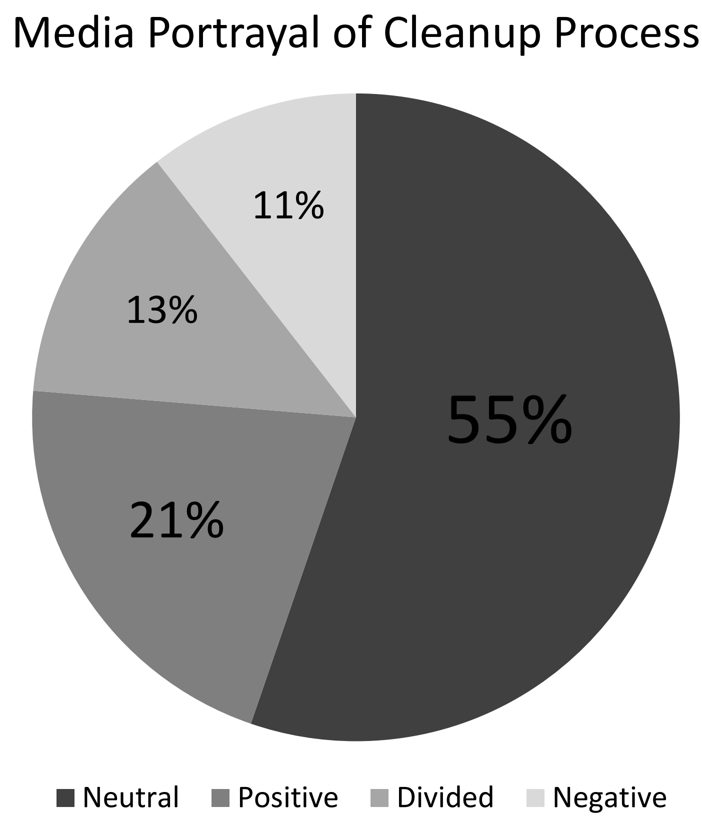


Figure 9. Tonal composition of local media coverage of cleanups

6.3 Benefit-Cost Analysis Results

Base calculations for the benefit-cost analysis are listed in Table 12. They clearly show that, under the scenario described in Section 5.3, the realized benefits of the cleanups greatly outweigh the costs of performing them. Between increased home sale revenue for sellers and increased tax revenue for the city, the elementary school cleanups led to $5,065,773 in benefits, compared to costs of $1,167,797. As described above, this does not necessarily account for the full benefit over time of these cleanups, but rather those realized as a result of delisting in particular. Still, the benefits accrued from this single treatment were nearly 5 times greater than the cost of cleanup. Clearly, the remediation of the 4 contaminated elementary schools in the Wenatchee School District were financially sound. Further, expedited remediation would have yielded significant returns to both homeowners and the City of Wenatchee tax base, as the benefits would have been realized sooner. Thus, the remediation of schools contaminated by lead and arsenic is economically efficient policy.

CHAPTER 7

DISCUSSION, POLICY, AND FURTHER WORK

7.1 Discussion of Results

While the magnitude and significance of impacts were highly variable, this is to be expected of such a large set of panel data and such a variety of model specifications. However, the overall trend of purchasing behavior as a result of school contamination and cleanup is clear. The announcement process, as represented by the announcement and listing treatment variables, had significant, negative impacts to area home values. And the end of remediation, as represented by the end of cleanup and delisting variables, yielded significant, positive impacts. Schoolyard remediation yielded a sizable, statistically significant, positive effect to home values with the greatest level of statistical significance observed across all model specifications at 6 months following the delisting of schools from the state's Hazardous Sites list. This demonstrates that the public a.) is receptive of official agency statements and hazard guidelines b.) trusts that remediation procedures were effective, and c.) believes that contaminated soil poses a significant enough risk to human health that they will pay more for homes in areas where schoolyards are free from it.

Of particular interest in this study is the fact that despite claims that soil contamination in the study area is understood as a "fact of life" (Steigmeyer 2001), the public dissemination of information in the forms of both agency announcements as well as media coverage both triggered negative purchasing responses from homebuyers. Thus, even though a hazard may be discussed among personal information networks, it would appear that consumers assign more significance to information that comes from official sources. This is in direct contrast to the findings of Wakefield and Elliot (2003) as well as those of Walsh and Miu's (2017). Walsh and Miu (2017) demonstrated that price effects of disclosure are contingent upon pre-existing awareness, and in cases where the contamination is widely known, there is sometimes no effect at all at the announcement stage. This study demonstrates that this cannot be said for all study areas nor all forms of contamination. Thus, it is clear that such information is valuable as a means of achieving information symmetry in the housing market, as well as to the development of efficient public policy. It is also notable that the *Wenatchee World* covered the entire cleanup process in a measured and objective way. For the most part, pieces that displayed obvious biases were either editorial or public comment.

7.2 Policy Implications

The basic policy implications of this study are clear. Cleanup yields far greater economic benefits – both public and private – than costs. Further, the sooner remediation is undertaken, the sooner homeowners and municipalities can reap the economic benefits of environmental quality in the housing market. The benefit-cost analysis from Section 5.3 makes this plain, and it is exponentially underscored by even a theoretical incorporation of the many public health studies cited in Section 3.5. Thus, this study strongly supports the notion that remediation of schoolyard soils contaminated with lead and arsenic is economically sound policy. However, the application of this policy is not nearly as discernible. As the work of the Task Force illuminated, the issue is as much a social one as it is an economic one. And, even as economic questions appear settled by the benefit-cost analysis above, funding sources for the state cleanup program that are both dependable and equitable remain difficult to identify.

First and foremost, Washington must determine an equitable means of adequately funding the Model Toxics Cleanup Act (MTCA). The current system of relying primarily on volatile oil markets is not only unsustainable, but also not entirely equitable. While legislation like FIFRA makes true equity a difficult target, a more efficient system is certainly possible. The MTCA currently collects revenue from the agrichemical industry via taxation, which is subject to neither FIFRA nor CERCLA. Thus, increased taxation on the manufacture, purchase, and application of hazardous agricultural chemicals is a potential means of funding the cleanup of the contamination caused by various industry actors, and one that is entirely within the purview of state government. Additionally, the state should actively seek funds from the federal government for the remaining cleanups, and from the United States Department of Agriculture in particular. The USDA was complicit in the creation of this problem and should therefore be a part of the solution.

Once funding is secured, the Department of Ecology should follow through on its intention to remediate at least those areas that are most frequented by children, namely parks and schools. While the quantitative figure provided by this study should, in theory, assuage the doubts and fears expressed by key stakeholders from the original Task Force, it is unlikely that such a uniformly rational response will materialize. Concerns about property values, agricultural stigma, and even food prices (if an additional agrichemical tax were proposed) would most certainly be raised. Thus, Ecology should employ a Coordinated Resource Management (CRM) plan in its statewide implementation of soil remediation. Rather than a statewide task force consisting of high-level officials, regional coalitions need to be formed in order for communities to determine their own levels of risk and abilities to deal with them. Objective, third-party facilitators need to be employed, so that conflict does not continue to breed inaction. In their Final Report, the Task Force stressed that “decisions about area-wide soil contamination should be made locally.” While this is clearly true, it needs to be integrated into a larger framework of resources in order for it to be a legitimate recommendation. The CRM approach allows state-level officials to engage local stakeholders at the individual community level and collaboratively determine the best approach to local remediation. It is a collaborative, consensus-based, stakeholder decision-making process that allows for greater regional empowerment and access to a larger and more diverse pool of knowledge and resources.

Washington has an Interagency CRM Executive Committee in place, and both the Department of Ecology and the Department of Agriculture are participating agencies

(WSCC n.d.). The model is currently being implemented to address issues such as rangeland management and wolf conservation. While area-wide soil contamination is not typical of the types of land use and resource issues that the model is normally applied to, the failure of the Task Force combined with the empirical success of the Wenatchee cleanups show a clear need for a stronger element of conflict management and public engagement in order to acquire the funding and political will to complete the cleanup process across the state.

There is no one-size-fits-all solution for such a complex, far-reaching, and potentially contentious issue, and the CRM model acknowledges that essential truth. It could serve to fill the gaps of the previous, state-level approach and employ a more collaborative, localized method. In doing so, it will take community-based experiences, perceptions, and worldviews into fuller consideration and place them in an appropriate regional context in order to counteract the notion that the various objectives of diverse stakeholders are mutually exclusive. This has the potential to fundamentally change the conversation about the issue and allow for local progress in place of a statewide stalemate. By securing additional, reliable, and more diverse funding, and by replacing a top-down solution with a coordinated approach, more than a decade of closed-door, bureaucratic inaction has the potential to be transformed into sustainable, regional progress that serves to bolster economic interests at both the state and local levels while simultaneously protecting the public from a serious health threat.

7.3 Further Work

The logical next step to evaluating public response to schoolyard remediation is to conduct a similar study using the cleanups undertaken 107 miles south of Wenatchee in Yakima, WA. Between 2003 and 2012, 7 schools and 2 parks were cleaned up in the city of Yakima. The inclusion of parks in the dataset would require a different geographic indicator for the proximity variable, but it would also offer new insights into the public's perception of contaminated soil. Yakima County is estimated to have 58,050 acres of contaminated soil, more than any other county in the state. In addition, a consideration of environmental justice and disproportionately affected populations would add considerable value to this work, especially because the majority of orchard workers in Washington are low-income Mexican immigrants and migrant workers.

On a broader level, there remains a serious need for epidemiological data on blood lead levels and lead poisoning across Washington State. As is detailed in Section 1.3, this urgent recommendation of the Task Force has yet to be heeded by the Washington Department of Health. Until reliable epidemiological data is collected, neither policymakers nor the public can make decisions with any degree of certainty. This data collection could – and should – be incorporated into any CRM planning program. The inclusion of additional study areas in the economic valuation of the remediation of contaminated soils, combined with the collection of blood-lead levels of children across the state, will allow for a more comprehensive understanding of the issue of area-wide soil contamination in Washington state and lead to the development and implementation of increasingly efficient policies to address it.

CHAPTER 8

JOURNAL ARTICLE

Get the lead out: A hedonic housing price analysis of soil contamination and remediation in Washington state

Jessica R. Martin and Toni Sipic

Central Washington University

Abstract

This study determines the economic impacts of soil contamination as a result of historical pesticide use in Wenatchee, WA. A hedonic regression analysis of home values before, during, and after cleanups of six contaminated schoolyards demonstrates the public's willingness to pay for remediated soil as a housing amenity. A qualitative analysis of media coverage of the contamination and cleanups confirms public awareness and categorizes public perception of risk. Results show a significant positive price effect following remediation, a negative media effect, and no observable stigma.

I. Introduction

From leaded gas to lead-based paint, the United States has a long history of delayed and/or inadequate policy responses to environmental lead contamination (Needleman 1991; Rabin 1998; Kovarik 2005). While gasoline and paint have consistently dominated the conversation about lead as a public health risk, soil is increasingly recognized as a critical exposure pathway. Therefore, public health experts, agency officials, and politicians at the highest levels of American public service have asserted that contaminated soil requires imminent, focused attention in order to protect the public and avoid repeating the policy mistakes of the past (Mielke and Reagan 1988; ASCTF 2003; Beauvais 2016; Clinton 2016).

While historical pollution from the combustion of leaded gas, dust from lead-based paint, and toxic industrial operations are key causes of soil contamination in urban areas, a lesser-known source affects hundreds of thousands of acres of rural land across the country. For the first half of the twentieth century, lead arsenate was the pesticide of choice for pome fruit orchards across the United States (Shepard 1951). The widespread and liberal use of this chemical has resulted in lead and arsenic contamination that persists in the soil under sites that have since been converted to homes, parks, and schools (Peryea 1998; Hood 2006; Schooley 2008). The Washington Department of Ecology (n.d.) estimates that nearly 200,000 acres of soil in the state of Washington are contaminated with persistent lead and arsenic as a result of ubiquitous statewide use of the pesticide from 1898 to 1948. According to the Natural Resource Conservation Service (NRCS) of the United States Department of Agriculture (2007), more than 10 million acres of cropland and nearly 7 million acres of rangeland were converted and developed across the United States between 1982 and 2007, suggesting that the frequency of issues regarding abatement liability for developers and property owners of formerly agricultural lands will only increase, and the determination of efficient actions will be ever more urgent. While simultaneously minimizing risk and conflict by keeping contaminated areas in agricultural production has been proposed as a solution to this problem (Peryea 1998), the figures from the NRCS indicate that it is not a realistic one. Thus, as development continues to expand to include more of these potentially contaminated sites, the consideration of public and private preferences will be critical to the decision-making process in regards to health risks and abatement actions.

Given that the hazards of lead exposure are suffered to a much greater extent by young children, in 2002 the Washington State Department of Ecology began testing parks and schools that are located on former agricultural land across the state. The results led to the statewide implementation of cleanups for a limited number of schools and parks. To date, no official evaluation of these cleanups has been undertaken, and tens of thousands of affected acres remain a public health risk while policymakers determine how to proceed in the face of debated risk and divided opinion. After these tests revealed levels of lead and arsenic well above the state’s acceptable limits for public exposure, six schools in the Wenatchee School District were included in the Washington Department of Ecology’s pilot cleanup response. A variety of remediation tactics were utilized at varying costs in 2006 and 2008 (ECY 2012). These cleanups were highly publicized, and opinions about their necessity were marked by the same polarity that has plagued American lead policy since the late 1800s (ASCTF 2003; Kling, Collins, and Marquis 2005; Warner 2005). Although it was covered by the Department of Ecology via the state Toxics Cleanup Program, the cost of remediation was a main point of contention throughout public discourse, as was the debated level of risk to public health.

This study provides a much-needed quantitative assessment of the impacts of soil contamination and remediation on property values in Wenatchee, WA and, thus, a definitive answer to the question of whether the cost of abatement is justifiable. By analyzing the relationship between area home values and their proximities to the contaminated school sites before, during, and after remediation, this study enumerates the public's willingness to pay for soil that is free of lead arsenate contamination via hedonic regression analysis. In addition, it serves to qualify public perception of risk in order to better understand how this affects consumer decision-making. Content analysis of local media coverage of the discovery, measurement, and remediation of school contamination serves to establish public awareness as well as to qualify the role of the media in the perception of environmental risk.

II. Previous Literature

By applying a hedonic price model to real estate values, Rosen (1974) demonstrated that housing prices, like the prices of all tradeable goods, are composite prices of a bundle of characteristics. Housing prices are affected by a variety of structural attributes, such as square footage, room count, fireplaces, pools, etc. They are also affected by neighborhood attributes, such as demographics, school quality, environment, and municipal services. Building on Lancaster's (1966) characteristics approach to consumer theory, Rosen's model (1974) showed that the implicit price of each individual characteristic of a house can be determined by regression analysis. Such an analysis allows for the identification of the price that homebuyers are willing to pay for specific, individual, non-tradeable goods, such as neighborhood services and environmental quality (Palmquist 1988). Thus, while there is no observable market for environmental quality, there is an implicit market for it as a characteristic of a home, and this can be measured by the regression of proxy variables. Because of this, the field of environmental economics has come to view hedonic housing price experiments as the optimal approach to evaluating environmental quality, as they utilize quasi-experimental, observational data to analyze the spatial and temporal impacts of contamination on home prices (Palmquist and Smith 2002).

Many studies have applied this method to air pollution, noise pollution, water quality, and, increasingly, soil contamination (Kohlhase 1991; Kiel 1995; Brasington and Hite 2005; Boyle et al. 2010; Mihaescu and von Hofe 2012). Most hedonic studies of toxic sites use proximity and/or public announcements as proxies for environmental quality. These studies consistently demonstrate a decrease in home values as a result of proximity to contamination (Boyle and Kiel 2001; McCluskey and Rausser 2003; Mihaescu and von Hofe 2012). Kolhase (1991) found that homebuyers were willing to pay a premium for increased distance from contaminated sites as a result of improved environmental quality and lower risk. However, proximity alone is insufficient as a proxy for environmental quality; there also needs to be a careful evaluation of the symmetry of information among stakeholders as part of any valid hedonic housing price study of environmental contamination (Guignet 2013).

Many hedonic studies of toxic sites identify a causal relationship between public dissemination of information and price signals and show prices falling and rebounding in direct response to content and timing (Kiel 1995; McCluskey and Rausser 2001; McCluskey and Rausser 2003; Boyle 2010). Several have demonstrated that the perception of risk, as inferred public announcements about potential contamination, is a greater driver of price effects than actual risk (McCluskey and Rausser 2003; Mastromonaco 2015; Andersson and Lavaigne 2016). While media may drive the public perception of risk and also be perceived as biased and/or unreliable (Slovic 1987; McCluskey and Rausser 2001; Wakefield and Elliot 2003), it is not the only source of information regarding environmental hazards. Agency announcements serve as unbiased, trustworthy, and heavily regulated sources of public information about the entire process of dealing with toxic sites (Kolhase 1991; Kiel 1995). Thus, failure to organize data into temporal groupings based on the dissemination of critical information released throughout the process of dealing with a toxic site could potentially miss the true source of a price signal (Kiel 1995). In other words, each new piece of procedural information - from initial announcement, throughout cleanup, up until remediation is officially deemed complete - should be utilized as a unique treatment variable.

Boyd et al. (2010) showed that the contamination of school sites in particular triggers a strong negative impact on nearby house prices. They also pointed out that, while private landowners are disincentivized to publicize contamination of their property, thus leading to an asymmetric market, schools must thoroughly publicize such a discovery. As a result, the announcement of school contamination was the driver of both awareness and price effects for their entire study area. This strongly supports the methodology of this study, which focuses specifically on school contamination as the causal factor of price effects in the study area.

Within the study of media coverage of environmental hazards and their associated risks, lead is frequently treated as a unique issue. Though this may change in coming years in light of the high-profile, events-based coverage of systemic water contamination in Flint, Michigan, the risks associated with lead contamination are not familiar to the average person. In their review of a randomized sample of 152 newspaper articles about lead contamination throughout the country, Brittle and Zint (2003) demonstrated that the media assumes that, because the public knows that lead is a hazard, it is not necessary to explain the risks, so they are not typically included in coverage of lead contamination. This is supported by Slovic's (2000) claim that even though lead is a fairly well known hazard, it is not understood enough to be dreaded. This behavior may be best explained by Tversky and Kahneman's (1973) theory of availability. Their work draws a connection between the level of risk an individual perceives in a given hazard and the availability of an example of someone in his/her personal network who has experienced the negative effects of a given hazard. Due to the insidious nature of lead poisoning, a personal example of it is not readily available to most people. This lack of familiarity has a discounting effect on risk perception. In other words, there is a “bias of imaginability” (Tversky and Kahneman 1973). Historically, people do not readily conceive of lead poisoning, and thus it is not widely feared.

III. Empirical Model

The main equation takes the following conceptual form:

$$\ln(P) = f(H,N,E)$$

where ln(P) is the natural log of the sale (all converted to 2015 dollars using the Western Urban Consumer Price Index from the Bureau of Labor Statistics); H is a vector of house-specific attributes; N is a vector of neighborhood attributes; and E is a proxy for environmental quality. The house-specific attributes are the structural features we obtained from the assessor data. The neighborhood attributes are captured by the Census block group ID variable. The proxy for environmental quality is the set of temporal remediation treatment variables. We grouped the regressions into two main categories: elementary schools and middle schools. While the high school was part of the cleanup program, there is only one high school in Wenatchee, so there is no control group by which to measure its effects; all houses in Wenatchee reside within the attendance boundary of the same high school.

We ran a second set of regressions that included a media variable but not the environmental treatment variables in order to avoid conflating effects, as the media frequently provides the first information to the public about a contamination event, and subsequent coverage contains much of the same information as official agency announcements. Thus, the media regression takes the following conceptual form:

$$\ln(P) = f(H, N, M)$$

where H still represents housing attributes, N still represents neighborhood characteristics, and M represents media information. In this case, M is an indicator variable that returns a 1 if there was an article published in the local newspaper that mentions the contamination and/or cleanup of the school associated with a sold house, and a 0 if there was not. The time intervals for the media variable are 0-30, 31-60, and 61-90 days prior to sale date in order to capture the short-term effects of media coverage on purchasing behavior.

For the functional forms detailed below, H, E, and M are carried over from the conceptual forms described above. Thus, β_x represents the set of coefficient estimates for various housing characteristics, namely age, square footage, garage square footage, and number of bedrooms. B_y represents the coefficient estimates of the cleanup treatment variables described in Section 4.2. β_z represents the set of coefficient estimates for the media variables in Form D. For all forms, λ represents the quarterly fixed effect, δ represents N in the form of Census block group fixed effects, and ϵ is the idiosyncratic error term. Subscripts i, j, and t indicate that each variable is affected by individual house, block group, and point in time, respectively.

Form A – Inclusive treatment variables grouped in 6-month intervals
(0-6 months from announce, 0-9 months from announce, … , 0-36 months from announce, all in one regression)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form measures the public's general reaction time by capturing the effect/s of each time interval across treatments, answering the question of which lag (6 months, 9 months, 12 months, … , 36 months) yields the greatest impacts across treatments.

Form B – Concentric treatment variables in a single regression
(0-6 months, 6-9 months, 9-12 months, … , 24-36 months)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

In this form, there is no temporal overlap among treatment variables, and they are all regressed in the same equation. It identifies the impacts of specific temporal ranges, as opposed to the impacts of overall lag as measured in Form A.

Form C – Concentric treatment variables grouped by treatment type
(0-6 months from announce, 6-9 months from announce, … , 30-36 months from announce, all in one regression)

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_y \beta_y E_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form uses the same concentric interval treatments as B, but they are grouped by treatment type. So, all announcement treatments are regressed together, all listing treatments are regressed together, etc. This form examines the effects of individual treatment types over time.

Form D - Media Treatment Variables Regressed Without Environmental Treatment Variables

$$\ln PRICE_{ijt} = \beta_0 + \sum_x \beta_x H_{ijt} + \sum_z \beta_z M_{ijt} + \delta_j + \lambda_t + \epsilon_{ijt}$$

This form captures the effect of media coverage of the contamination on homebuyer's purchasing choices at 0-30, 31-60, and 61-90 days leading up to the sale.

We ran a fixed effects regression analysis of housing attributes and sale prices using the statistical analysis software program Stata. The fixed effects model controls for time invariant, unobservable attributes in order to avoid omitted variable bias. Based on its predominance in the literature as a means of addressing heteroskedasticity and its ability to control for large variations in housing prices, (Le Goffe 2000, Boyle 2010, Mihaescu and Hofe 2012), we applied the log-linear form of robust regression in Stata, using the natural log of the sale price as the dependent variable. Robust standard errors enable us to identify unbiased standard errors of the coefficients despite unknown heteroskedasticity in the model. Thus, by applying the log-linear model to ordinary least squares regression, and by reporting robust standard errors, we are able to account for autocorrelation and variable distribution of the errors terms themselves.

In order to control for spatial auto-correlation, which occurs when the price of a house is dependent upon the prices of houses near it, we included a factor variable of the Census block group number for each house. Similarly, we included a factor variable for time and market factors by concatenating sales year and sales quarter into a single variable called "quarteryear," to control for temporally fluctuating housing market variables that are not otherwise captured by the data but vary quarterly. Finally, we clustered the data around school attendance boundaries in order to account for the inherent variability in housing prices across this key geographic indicator for the study. These parameters, along with the robust regression form, impose strict controls on the data in order to yield the most reliable results.

Rather than utilizing Euclidean distance and buffers to measure effects in relation to proximity, as is common in hedonic housing price models, the nature of this study lends itself to a unique geographic variable in the form of school attendance boundaries. This allows us to indicate with a simple yes or no indicator variable whether or not a certain house was sold within the attendance boundary of a contaminated school during treatment/s. Due to the immobility of the contaminants, the hazard is treated as contained to specific sites. This - combined with the facts that lead has an inordinately negative effect on the health of children in particular, and children are most likely to ingest soil particles through play - reasonably lead to the conclusion that those most at risk are the students at contaminated schools, and this is most effectively captured by attendance boundaries. According to Wenatchee School District policy 3130, “students shall attend the school designated for their respective residential area,” (WSD 2015). Some amendments have been made to the policy in recent years in order to increase choice with an aim to help alleviate issues of crowding and class size, but these were not in place during the timeframe of this study. So, the vast majority of students attended the schools assigned to their homes, and homebuyers had no reason to believe their own children would not do the same.

We obtained school district boundary maps from the Wenatchee School District Office of the Superintendent and digitized them as shapes in ArcGIS for use as an overlay with the parcel maps obtained from the Chelan County Assessor. Using the Intersect tool in Arc GIS, we assigned each housing sale a geographic variable named for the school that would be attended by any children residing in the home. Thus, the treatment group becomes those houses sold within the attendance boundaries of schools that were contaminated and subsequently remediated, and the control group is composed of houses sold within the boundaries of schools that were not contaminated. We confined our data to the city limits of Wenatchee, because countywide data introduced too great a degree of uncontrollable variability, due to the stark socioeconomic and geographic differences between the two areas. We assert that the most empirically defensible quasi-experimental model for this research question is derived from city-level sales data segmented by school attendance boundaries.

IV. Media Analysis

Between 2001 and 2010, the *Wenatchee World* printed 40 stories pertaining to the issue of lead arsenate soil contamination in the Wenatchee area. In 2002, the Department of Ecology tested all schoolyards in the Wenatchee School District for contamination. By the end of 2010, remediation of all affected schools had been completed, and all schools in the district were removed from the state's Hazardous Sites List. Thus, this timeframe is inclusive of the discovery of contamination and the start and end dates of all remediation actions. These three events, specific to each school and, thus, also to each home, serve as the basis for the key treatment variables in the regression analysis and are therefore the focus of the media analysis.

The Wenatchee Public Library has a digital archive of all *Wenatchee World* articles, with an unexplained gap from September through December of 2002. We accessed articles from this time period via the microfilm collection at the Wenatchee Public Library. We copied and pasted article content from the digital archives and transcribed articles from the microfilm collection into individual Microsoft Word documents in order to upload them into Atlas.TI, a computer-aided qualitative data analysis program. Articles were tabulated by date and the names of contaminated schools that were specifically mentioned in each one. We created the media variable based on 1.) the mention of a specific school, 2.) the attendance boundary for that school, and 3.) the days from article publication to date of sale. Thus, the media variable is actually a set of three dummy variables that deliver a 1 if there was a newspaper article within 30, 60, or 90 days of the sale date of a home that resides within the attendance boundary of a contaminated school that was mentioned by name in the article/s, and a 0 if there was not. This captures the short-term effect of people's perceptions of risk in response to media coverage of a hazard.

After collecting the above detailed data on local newspaper coverage of the contamination and cleanups, we performed an in-depth content analysis of the articles in order to qualify the media information that potential homebuyers in Wenatchee were apprehending. Content analysis is one of many ways of analyzing qualitative, textual data; others include ethnography, grounded theory, phenomenology, and historical research (Hsieh and Shannon 2005). The method expands upon more simplistic analytical approaches like word counts and seeks to identify the concepts, ideas, and relationships present within the context of linguistic themes and expressions in order to infer their impacts (Weber 1990). Hsieh and Shannon (2005) define content analysis as "a research method for the subjective interpretation of the content of text data through the systematic classification process of coding and identifying themes or patterns" (p.1278). Codes are designated thematic concepts that are identified and deemed significant by the researcher, hence the subjective nature of the method. Passages of the text in question are then assigned codes as befits them, and relationships are identified by semantic associations of cause and effect. Hsieh and Shannon (2005) identify three main types of content analysis: conventional, directive, and summative. We adhered to their above quoted definition of the method and employed the conventional approach as they posit it, avoiding pre-conceived notions of the content and allowing categories and codes to emerge from the data itself rather than from a particular theoretical framework.

We used a computer aided qualitative data analysis (CAQDA) program called Atlas.TI in order to perform this analysis. CAQDA is a methodology that allows researchers to utilize specialized software in order to better identify, organize, and visualize relationships among various codes and categories and to make inferences as to their significance. By conducting a computer-aided media analysis in addition to regressing the media variable with the housing and cleanup data, we were able to answer two key questions: 1.) Did media coverage of the contamination and cleanups effect consumer behavior? and 2.) Was the coverage sensationalized and/or biased, as much media coverage of environmental hazards has been accused of being? The first question is answered by the coefficient of the media variables in the regression analysis, and the second question is answered by the content analysis.

V. Data

Housing Data

Housing data includes detailed information on sales, structural attributes, and location. All of this is publicly available from the Chelan County Assessor, in the form of sales prices and dates, structural features, and parcel maps. This online database served as the source of all housing data for this study. The raw sales data was organized and processed in Microsoft Excel according to structural attributes (square footage, bedroom count, age, garage), sale price, and location. The sales price serves as the dependent variable in the regression equation, and the structural and neighborhood features make up a portion of the set of independent variables. We know that these characteristics significantly affect the price of a home, and, by controlling for them, we aim to enumerate the precise price effect of environmental quality, with remediation process dates serving as the proxy variables. We constrained square footage to a maximum of 3052 for elementary schools and 3050 for middle schools (calculated using Q3 + 1.5IQR) in order to remove the effects of outliers. There were no outliers at the low end of square footage, so there was no need to constrain the data to a minimum area. We included a squared covariate of the age term in order to capture the non-linear effects of this variable. In order to control for neighborhood attributes and spatial autocorrelation, which are not specifically detailed in the housing sales data, we utilized publicly available, block-level U.S. Census data (Parmeter and Pope 2009). Summary statistics for the housing data are listed in Tables 1-3.

TABLE 1
Summary Statistics for All Elementary School Regressions (n=10080)

Variable	Mean	Std. Dev.	Min	Max
Price (in 2015$)	194842.3	125164.1	25195	1600000
Floor Area (in sq.ft)	1504.15	517.7998	276	3051
Bedrooms	2.920833	0.8399458	1	9
Age (in years)	49.8378	30.42196	2	115
Garage Area (in sq.ft)	377.3395	267.6602	0	2304

TABLE 2
Summary Statistics for All Middle School Regressions (n=9800)

Variable	Mean	Std. Dev.	Min	Max
Price (in 2015$)	194980.3	125493.3	25195	1600000
Floor Area (in sq.ft)	1503.846	517.4219	276	3051
Bedrooms	2.919848	0.8385668	1	9
Age (in years)	49.74962	30.45637	2	115
Garage Area (in sq.ft)	377.2483	267.5311	0	2304

TABLE 3
Single Family House Prices by School in Wenatchee, WA

School	Count	Mean	Std. Dev.	Min	Max
Elementary					
Columbia	1578	147886.5	52254.48	28470	444468
John Newbury	1912	219436	122201.9	38024	1300000
Lewis and Clark	1218	171460.8	57131.54	25195	536827
Lincoln	1850	189282.4	82978.22	30000	710387
Mission View	533	251683.5	371166.3	41948	1600000
SunnySlope	467	264738.6	134765.7	39020	813830
Washington	2522	195991.8	82674.8	38190	694481
Middle					
Foothills	3317	215046.7	112815.1	38024	1300000
Orchard	3420	175252.1	78773.51	25195	694481
Pioneer	3243	195254.8	167603.9	38190	1600000

Note: All prices in 2015 $.

Cleanup Data

School cleanup data provides two key sets of variables: 1.) a geographic variable to compare with housing data and 2.) the treatment variables, in the form of cleanup process dates. As described above, the geographic variable is defined as the school attendance boundary. The second set of school data is the actual contamination and cleanup data. We collected information on the 6 remediation sites from the Washington State Department of Ecology and catalogued it according to location, timing, contamination level, and cleanup type. The 5 key temporal variables (the treatments in the regression model) for contaminated sites are Announcement, Listing, Cleanup Start, Cleanup End, and Delisting. Table 4 details the timing and duration of the five cleanup treatment variables for each school.

TABLE 4
Cleanup Treatment Variables

School Name	*Announce*	*List*	*Cleanup Start*	*Cleanup End*	*Delist*
Washington Elem.	11/10/03	8/2/04	7/1/06	9/12/06	12/17/07
Lincoln Elem.	11/10/03	8/2/04	6/10/06	9/1/06	12/17/07
Sunnyslope Elem.	11/10/03	2/7/05	3/29/07	9/30/08	2/12/10
Lewis & Clark Elem.	11/13/03	1/26/06	7/1/06	8/1/06	12/17/07
Orchard Middle	11/13/03	1/26/06	3/29/07	12/31/08	2/12/10

The Announcement variable is the date that the public was first made aware of the contamination. The Department of Ecology sent an “Early Notice” letter to the superintendent of the Wenatchee School District for each of the contaminated schools. The date of the letter serves as the Announcement treatment variable for this study. However, it is not possible to fully measure the level of public awareness that resulted from this letter, and some studies indicate a countervailing effect of such announcement variables, in that the inherent promise of remediation may trigger either a negative price effect in response to fears of a potential hazard, or it may actually increase area property values due to the assumption that cleanup is imminent (Gamper-Rabindran and Timmins 2013). In addition, local media coverage in Wenatchee offered earlier indications of a contamination problem at all six schools. The media variable described above serves to capture the effects of this. Finally, all “Early Notice” letters were sent in November of 2003, and the first cleanups did not commence until summer of 2006; this lag may have swayed the public's understanding of the severity of the contamination and thus their perceptions of risk. So, the agency-issued announcement is included as a treatment variable, as is standard in the literature, but it is expected to yield ambiguous and/or insignificant price effects for the reasons stated above.

Similarly, the Listing variable is the date on which the Department of Ecology added the site to the state's Hazardous Sites List, but the public effects of a largely procedural milestone with unstated consequences are unclear. Furthermore, the lag between listing and Cleanup Start is highly variable, with remediation beginning four months after listing for one school and more than two years afterward for several others. This disparity likely served to further confuse the public in regards to the practical meaning of the listing action, and thus hampered their ability to assess its implications for risk. And, Gamper-Rabindran and Timmins (2013) assign the same potential for countervailing effects to the Listing variable as they do to the Announcement variable. In short, there are several inferences the public can draw from these two variables, and the variable lag time that existed for both Announcement and Listing in this study may serve to further confound the public.

The Cleanup Start variable marks the beginning of the onsite remediation process for each school and is thus the first publicly visible indication that a.) the risk is/has been real, and b.) a process is underway to mitigate it. If the public believes that the cleanup will be sufficient to remove the risk from the site, then this should trigger a positive effect. However, if there is especially strong stigma associated with the contamination and its risks, or if there are doubts about the efficacy of the cleanup process, this variable will have no effect. The Cleanup End variable marks the completion of remediation; as such, it will likely server to underscore the effects of the Cleanup Start variable.

While it is part of the same set of agency-issued, mandated communications, the Delisting variable differs from Announcement and Listing in that the implications are unequivocal: the cleanup process is complete, and the site has officially been declared safe by the Department of Ecology. A site is only delisted once it can be assigned a “No Further Action” status from Ecology, meaning cleanup was successful, and contaminant levels are below the acceptable thresholds. This is a highly publicized designation. Per the literature, this variable should elicit a positive price response that serves as a rebound to any negative response that occurred earlier in the treatment timeline. A negative response would be highly unexpected in this situation, as it is clear in the literature on risk perception (prior to high-profile events like the 2016 contamination of the water supply in Flint Michigan) that stigma around lead is low (Slovic 2000). So, barring a complete lack of confidence in the state’s ability to effectively remediate the contamination, the response to delisting should be positive and significant.

Each of the 5 treatment variables is measured at 3, 6, and 9 months from the initial dates to measure short term effects, and also at 12, 18, 24, 30, and 36 months in order to capture any lag in public response or long term stigma. So, there totals 8 inclusions of each individual temporal treatment variable in the regression analysis in order to capture effects at a progression of dates from the initial Announcement, Listing, Cleanup Start, Cleanup End, and Delisting dates. This allows for the capture of both short- and long-term price effects, and should measure the public's initial response to each treatment as well as identify any long-term impacts that would be attributed to irreconcilable stigma. We included models in which temporal ranking of treatments was concentric (i.e. 0-6, 6-9, 9-12) as well as inclusive (i.e. 0-6, 0-9, 0-12…) in order to capture the widest variety of temporal effects. All regressions were confined to school type, elementary or middle. We regressed concentric temporal treatments collectively in one regression as well as by treatment type, and then ran inclusive temporal treatments grouped by temporal demarcation.

V. Results

Regression Results

The results for the elementary school group were unequivocal, with consistent signs (of varying magnitude and significance) across all models. The models show that, even under a variety of model specifications, impacts of treatment variables prior to the start of cleanup were largely negative, and impacts of treatments following the cleanups were largely positive. While significance and magnitude varied (see Appendix for full results), the signs were consistent with the literature in all functional forms. These findings are easily explained by the fact that the coefficients of variables like announcement and listing function as signals that a hazard is present, and consumers respond to the risks associated with that hazard. Similarly, variables such as end of cleanup and delisting from the state's Hazardous Sites List marked a collectively perceived end to the risks associated with contamination, and they are in line with the literature on rebounding real estate prices in contaminated and remediated areas. The most consistently significant impacts were those of the delisting treatment variable. At 6 months after delisting, there was a significant, positive impact of approximately 5% in all elementary school models. Table 5 illustrates the impacts observed at 6 months from delisting across functional forms of the elementary school regression model.

TABLE 5
Elementary School Regression Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.042	-0.060	-0.070	-0.095	-0.105	-0.098	-0.098
	(0.060)	(0.068)	(0.056)	(0.054)	(0.058)	(0.055)	(0.062)
Listed	0.011	-0.008	0.077	0.064	0.027	0.012	-0.015
	(0.041)	(0.041)	(0.048)	(0.040)	(0.040)	(0.048)	(0.036)
Started	-0.009	-0.055	-0.056	-0.072	0.025	0.044	0.131*
	(0.097)	(0.054)	(0.074)	(0.058)	(0.048)	(0.052)	(0.063)
Ended	0.052	0.079*	0.053	0.050	0.007	0.007	-0.036
	(0.062)	(0.035)	(0.055)	(0.051)	(0.056)	(0.085)	(0.099)
Delisted	0.054**	0.047**	0.031	-0.072	-0.038	-0.052	-0.065
	(0.020)	(0.019)	(0.026)	(0.122)	(0.103)	(0.092)	(0.025)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.309	0.310	0.310	0.310	0.310	0.311

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

TABLE 6
Elementary School Regression Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.045	0.016	0.015	0.015	0.052**
	(0.059)	(0.034)	(0.075)	(0.075)	(0.018)
6-9 months	-0.040	-0.029	-0.067	-0.067	0.078
	(0.063)	(0.059)	(0.053)	(0.053)	(0.090)
9-12 months	-0.080	0.179	0.004	0.004	-0.052
	(0.076)	(0.153)	(0.049)	(0.049)	(0.081)
1-1.5 years	-0.130*	-0.021	0.007	0.007	-0.177
	(0.058)	(0.029)	(0.036)	(0.036)	(0.236)
1.5-2 years	-0.135*	-0.068	0.156*	0.156*	0.029
	(0.059)	(0.044)	(0.067)	(0.067)	(0.064)
2-2.5 years	-0.078	-0.081	0.035	0.035	-0.056
	(0.064)	(0.061)	(0.088)	(0.088)	(0.042)
2.5-3 years	-0.051	-0.033	0.161	0.161	0.002
	(0.080)	(0.047)	(0.103)	(0.103)	(0.031)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.311	0.311	0.309	0.310

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

The results of the middle school regression were slightly more ambiguous. Overall, impacts were less consistent within treatment types and across models. While the announcement and delisting variables generally yielded negative impacts, the end of cleanup yielded positive and negative impacts of varying magnitudes at different temporal markers. However, overall, the pre-cleanup treatments produced negative impacts, and the post-cleanup treatments yielded positive impacts, and all significant results follow this trend.

TABLE 7
Middle School Regression Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.035	-0.094	-0.073	-0.071	-0.087	-0.078	-0.082
	(0.052)	(0.058)	(0.064)	(0.078)	(0.079)	(0.078)	(0.074)
Listed	0.025	0.003	-0.011	0.017	-0.018	-0.003	0.010
	(0.031)	(0.032)	(0.024)	(0.013)	(0.019)	(0.016)	(0.012)
Started	-0.290	-0.162	-0.107	-0.070	-0.049	-0.028	-0.064
	(0.265)	(0.127)	(0.095)	(0.057)	(0.039)	(0.028)	(0.022)
Ended	0.080	0.125	0.061	0.060	0.049	-0.040	-0.011
	(0.082)	(0.097)	(0.083)	(0.036)	(0.028)	(0.042)	(0.051)
Delisted	-0.009	0.008	-0.004	0.021	0.014	0.039	0.043
	(0.017)	(0.008)	(0.021)	(0.022)	(0.047)	(0.072)	(0.073)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980	9,980	9,980
R-squared	0.311	0.310	0.310	0.310	0.310	0.310	0.310

Note: Robust standard errors in parentheses, clustered on middle school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

TABLE 8
Middle School Regression Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.050	0.022	-0.292	0.084	-0.004
	(0.065)	(0.034)	(0.27)	(0.082)	(0.012)
6-9 months	-0.209*	-0.035	-0.006	0.187	0.053
	(0.069)	(0.029)	(0.047)	(0.120)	(0.033)
9-12 months	-0.007	-0.046**	0.017	-0.133	-0.024
	(0.102)	(0.007)	(0.032)	(0.049)	(0.065)
1-1.5 years	-0.073	0.018	0.018	0.068*	0.122
	(0.113)	(0.062)	(0.032)	(0.019)	(0.057)
1.5-2 years	-0.141	-0.159**	-0.002	0.014	0.0503
	(0.076)	(0.017)	(0.026)	(0.025)	(0.112)
2-2.5 years	-0.043	0.015	0.027	-0.217	-0.015
	(0.086)	(0.051)	(0.044)	(0.157)	(0.023)
2.5-3 years	-0.073	-0.166*	-0.156*	0.038	0.069**
	(0.053)	(0.055)	(0.044)	(0.032)	(0.014)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980
R-squared	0.310	0.310	0.312	0.311	0.309

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

There are three middle schools in the Wenatchee School District, and only one was treated. This marks the key difference in the data between the middle and elementary school groups. There are seven elementary schools in the district, and four were treated. Thus, the elementary school effects were aggregated from home sales across four different attendance boundaries and over a period from 2004 to 2013, resulting in a higher quality sample with greater exogeneity. The middle school group includes only one treated school, and the treatment spans from 2006 to 2013, with an inordinate lag between treatment variables. In particular, the cleanup period for Orchard Middle School lasted from March 29, 2007 until December 31, 2008, amounting to a 16-month lag between cleanup start and cleanup end. With the exception of Sunnyslope, elementary school cleanup periods lasted just 1-3 months. It is possible that this long period of action is indicative of an especially complicated and/or unsuccessful cleanup, and this could explain negative price impacts associated with its ending. If the cleanup of this particular school was not well understood, or if the public believed it to be unsuccessful, then the completion of the process could very well trigger a negative price effect. However, there is no empirical evidence for or against this claim in either the cleanup or the media data.

As illustrated by Functional Form D in Section 5.1, we regressed the three media variables separately from the environmental treatment variables to avoid capturing conflating effects with the environmental treatment variables. This equation shows clearly that the media coverage of the school cleanups in Wenatchee did in fact have an impact on purchasing decisions. At each time interval, there was a negative impact to home prices, with the most significant results measured at 31-60 days from sale date. These results are detailed in Table 7. This is in line with results from the environmental treatment variables as well – there are clear negative impacts to house prices during the announcement, listing, and pre-cleanup phase. When people become aware of the hazard, they are able to respond in their purchasing behavior. This is also consistent with the literature. Even though the presence of lead and arsenic in north central

Washington soils was considered a fairly well-known reality (Steigmeyer 2001), the dissemination of official information, whether by agency or media, still served to elicit novel responses from homebuyers. However, it is important to note that the 9.3% negative impact that resulted from media coverage at 31-60 days before sale date is far greater than any impact from the agency-issued treatment variables, indicating that homebuyers in Wenatchee, WA are influenced more by information in the local newspaper than by agency-issued proclamations.

TABLE 7
Media Regression Results (n=11,681)

Days between article publication and sale date	Coefficient
0-30	-0.0512
	(0.0358)
31-60	-0.0933**
	(0.0284)
61-90	-0.0321
	(0.0554)
Constant	10.67***
	(0.0534)
R-squared	0.292

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

Content Analysis Results

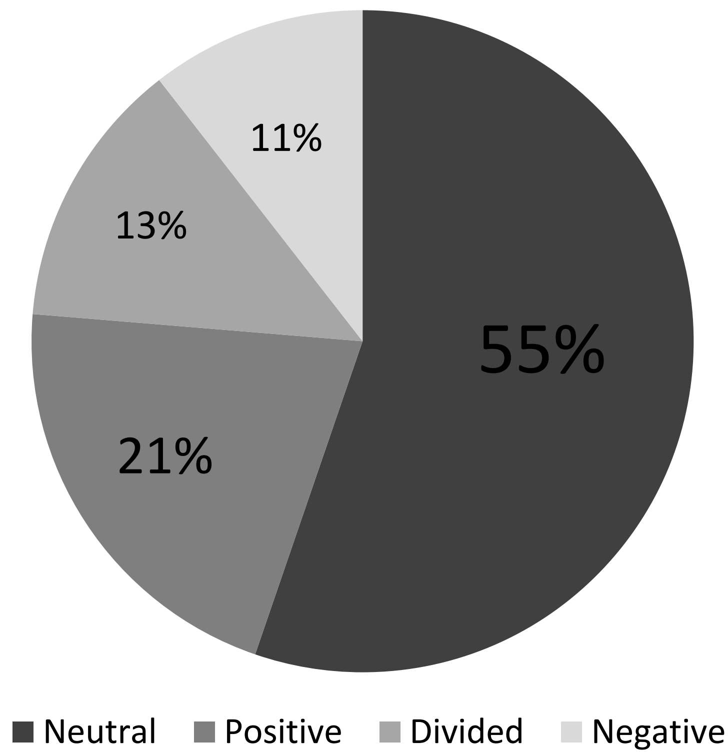
As is made clear in the literature reviewed in Section II, the public forms a set of beliefs about potential risk as a result of a variety of sources of information, and the role of media coverage is still debated among researchers. Our analysis showed that, by and large, local newspaper coverage of the contamination and cleanups in Wenatchee, WA was objective and focused on three key practicalities: the source of the contamination (orchards), the fact that the contamination poses a public health risk (of debated severity), and the cost of remediation (borne by either the school district or the Department of Ecology). The software we used allows for the identification of code co-occurrences, so that researchers can determine the relationships between pairs of key themes. The co-occurrence of codes in the *Wenatchee World* coverage of the contamination and cleanup revealed strong relationships between the themes of cost and liability, expert opinion and the presence of risk, and expert opinion and the source of contamination.

TABLE 8
Frequency of Most Used Code Co-Occurrences

Primary Code	*Co-occurring code*	*Frequency of Co-occurrence*
Expert	Risk = yes	29
Expert	Source = orchards	27
Expert	Medical effects	11
Expert	Hazardous = yes	10
Lead Arsenate	Source = orchards	11
Risk = yes	Medical effects	11
Cost (state)	Cleanup	10
Cost (general)	Contamination	10

These relationships are easily explained by objective factors and are in line with the key themes described above. The question of cost was frequently discussed in terms of liability, because the costs were great, and there was a concern that they would be incurred at the local level, by the school district, rather than by the Department of Ecology. The risks associated with the contamination, along with the source of the contamination, were both frequently included in the form of direct quotes from expert sources and official statements by government agencies rather than public opinions and anecdotal claims. While the level of risk was never clearly identified in the media, nor was it possible for it to have been, the fact that it was frequently described and discussed by public health and environmental experts resulted in a fairly measured debate. This is likely one of the key reasons that the *Wenatchee World* coverage proved to be more objective than the literature suggests is typical for such events. Figure 1 enumerates the number of articles that portrayed the cleanup process as positive, negative, neutral, or divided.

FIGURE 1
Tonal Composition of Local Media Coverage of Cleanups



V. Conclusion and Discussion

While the magnitude and significance of impacts were highly variable, this is to be expected of such a large set of panel data and such a variety of model specifications. However, the overall trend of purchasing behavior as a result of school contamination and cleanup is clear. The announcement process, as represented by the announcement and listing treatment variables, had significant, negative impacts to area home values.

And the end of remediation, as represented by the end of cleanup and delisting variables, yielded significant, positive impacts. Schoolyard remediation yielded a sizable, statistically significant, positive effect to home values with the greatest level of statistical significance observed across all model specifications at 6 months following the delisting of schools from the state's Hazardous Sites list. This demonstrates that the public a.) is receptive of official agency statements and hazard guidelines b.) trusts that remediation procedures were effective, and c.) believes that contaminated soil poses a significant enough risk to human health that they will pay more for homes in areas where schoolyards are free from it.

Of particular interest in this study is the fact that despite claims that soil contamination in the study area is understood as a "fact of life" (Steigmeyer 2001), the public dissemination of information in the forms of both agency announcements as well as media coverage both triggered negative purchasing responses from homebuyers. Thus, even though a hazard may be discussed among personal information networks, it would appear that consumers assign more significance to information that comes from official sources. This is in direct contrast to the findings of Wakefield and Elliot (2003). Thus, it is clear that such information is valuable as a means of achieving information symmetry in the housing market, as well as to the development of efficient public policy.

The basic policy implications of this study are clear. Cleanup yields a positive, significant benefit that is realized by the private market as increased home values and, in turn, by the public sector as increased property tax revenue. Further, the sooner remediation is undertaken, the sooner homeowners and municipalities can reap the economic benefits of environmental quality in the housing market. The results of this analysis make this plain, even without the inclusion of any of the measurable public health or social costs of toxic exposure. Thus, agencies, municipalities, and the real estate market alike would be best served by policy instruments that hasten the cleanup of sites contaminated with lead and arsenic.

REFERENCES (JOURNAL ARTICLE)

Andersson, Henrik, and Emmanuelle Lavaine. 2016. "Nitrates and People Perception: A Hedonic Application."

Area-Wide Soil Contamination Task Force (ASCTF) *"Area-Wide Soil Contamination Task Force Final Report." Area Wide Soil Contamination Task Force.* 2003. Accessed April 23, 2017 http://www.ecy.wa.gov/programs/tcp/area_wide/Final-Report/PDF/TF-Report-final.pdf

Boyle, K. J., N. V. Kuminoff, C. Zhang, M. Devanney, and K. P. Bell. 2010. "Does a Property Specific Environmental Health Risk Create a "Neighborhood" Housing Price Stigma? Arsenic in Private Well Water.: Water Resources Research 46, W03507, doi:10.1029/2009WR008074.

Boyle, Melissa and Katherine Kiel. 2001. "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities." *Journal of Real Estate Literature 9* (2): 117-144.

Brasington, David M. and Diane Hite. 2005. "Demand for Environmental Quality: A Spatial Hedonic Analysis." *Regional Science and Urban Economics.* 35 (1): 57-82.

Brittle, Christine and Michaela Zint. 2003. "Do Newspapers Lead with Lead? A Content Analysis of How Lead Health Risks to Children are Covered." *Journal of Environmental Health* 65 (10): 17-22.

Democratic Presidential Primary Debate. CNN. Flint, MI. March 7, 2016. 8:00 p.m. EST Statement by Secretary of State Hilary Clinton. Full transcript available at: http://cnnpressroom.blogs.cnn.com/2016/03/06/final-rush-transcriptcnndemocratic-presidential-primary-debate-flint-mi/

Examining Federal Administration of the Safe Drinking Water Act in Flint, MI: Hearing before the Full House Committee on Government Oversight and Reform. 114th Congress. 1. February 3, 2016. 11:47a.m. EST. Testimony of Mr. Joel Beauvais, Acting Deputy Assistant Administrator, Office of Water, Environmental Protection Agency.

Gamper-Rabindran, Shanti and Christopher Timmins. 2013. "Does Cleanup of Hazardous Waste Sites Raise Housing Values? Evidence of Spatially Localized Benefits." *Journal of Environmental Economics and Management* 65 (3): 345-360.

Guignet, Dennis. 2013 “What do Property Values Really Tell Us?: A Hedonic Study of Underground Storage Tanks.” *Land Economics* 89 (2): 211-226.

Hood, Ernie.2006. "The Apple Bites Back: Claiming Old Orchards for Residential Development." *Environmental Health Perspectives* 114 (8): A470.

Hsieh, Hsiu-Fang and Sarah E. Shannon. 2005. "Three Approaches to Qualitative Content Analysis." *Qualitative Health Research* 15 (5): 1277-1288.

Kiel, Katherine A. 1995. "Measuring the Impact of the Discovery and Cleaning of Identified Hazardous Waste Sites on House Values." *Land Economics* 71 (4): 428-435.

Kling, Barry, Frank Collins, and Mark Marquis. "Take Lead and Public Health Seriously." *Wenatchee World* (Wenatchee, WA), October 9, 2005. Accessed December 10, 2015. http://www.wenatcheeworld.com/news/2005/oct/09/take-lead-andpublichealth-seriously/

Kohlhase, Janet E. 1991. "The Impact of Toxic Waste Sites on Housing Values." *Journal of Urban Economics* 30 (1): 1-26.

Kovarik, William. 2005. "Ethyl-Leaded Gasoline: How a Classic Occupational Disease Became an International Public Health Disaster." *International Journal of Occupational and Environmental Health* 11 (4): 384-397.

Lancaster, Kelvin J. 1966. "A New Approach to Consumer Theory." *Journal of Political Economy* 74 (2): 132-157.

Le Goffe, P. 2000. “Hedonic Pricing of Agriculture and Forestry Externalities.” *Environmental and Resource Economics* 15(4): 397-401.

McCluskey, Jill J., and Gordon C. Rausser. 2001. "Estimation of Perceived Risk and its Effect on Property Values." *Land Economics* 77 (1): 42-55.

McCluskey, Jill J. and Gordon C. Rausser. 2003. “Hazardous Waste Sites and Housing Appreciation Rates.” *Journal of Environmental Economics and Management 45* (2): 166-176.

Mielke, Howard W., and Patrick L. Reagan. 1998. "Soil is an Important Pathway of Human Lead Exposure." *Environmental Health Perspectives* 106 (1): 217.

Mihaescu, Oana, and Rainer vom Hofe. 2012. "The Impact of Brownfields on Residential Property Values in Cincinnati, Ohio: A Spatial Hedonic Approach." *Journal of Regional Analysis & Policy* 42 (3): 223.

Needleman, Herbert L. 1991. "Childhood Lead Poisoning: A Disease for the History Texts." *American Journal of Public Health* 81 (6): 685-687.

REFERENCES (COMPLETE)

Abernathy, Charles O., Yung-Pin Liu, David Longfellow, H. Vasken Aposhian, Barbara Beck, Bruce Fowler, and Robert Goyer. 1999. "Arsenic: Health Effects, Mechanisms of Actions, and Research Issues." *Environmental Health Perspectives* 107 (7): 593.

Andersson, Henrik, and Emmanuelle Lavaine. 2016. "Nitrates and People Perception: A Hedonic Application."

Area-Wide Soil Contamination Task Force (ASCTF) *"*Area-Wide Soil Contamination Task Force Final Report." *Area Wide Soil Contamination Task Force.* 2003. Accessed April 23, 2017 http://www.ecy.wa.gov/programs/tcp/area_wide/Final-Report/PDF/TF-Report-final.pdf

Billings, Stephen B., and Kevin T. Schnepel. 2017. "The Value of a Healthy Home: Lead Paint Remediation and Housing Values." *Journal of Public Economics* 153: 69-81.

Bonnieux, François, Alain Carpentier, and Robert Weaver. 1998. "Reducing Soil Contamination: Economic Incentives and Potential Benefits." *Agriculture, Ecosystems & Environment* 67 (2): 275-288.

Boyle, K. J., N. V. Kuminoff, C. Zhang, M. Devanney, and K. P. Bell. 2010. "Does a Property Specific Environmental Health Risk Create a "Neighborhood" Housing Price Stigma? Arsenic in Private Well Water.: Water Resources Research 46, W03507, doi:10.1029/2009WR008074.

Boyle, Melissa and Katherine Kiel. 2001. "A Survey of House Price Hedonic Studies of the Impact of Environmental Externalities." *Journal of Real Estate Literature 9* (2): 117-144.

Brasington, David M. and Diane Hite. 2005. "Demand for Environmental Quality: A Spatial Hedonic Analysis." *Regional Science and Urban Economics.* 35 (1): 57-82.

Brittle, Christine and Michaela Zint. 2003. "Do Newspapers Lead with Lead? A Content Analysis of How Lead Health Risks to Children are Covered." *Journal of Environmental Health* 65 (10): 17-22.

Centers for Disease Control and Prevention (CDC). "Lead." Updated October, 2016. Accessed May 13, 2017. http://www.cdc.gov/nceh/lead/default.htm

Center for the New West. 2000. “Wenatchee: A High Performance Community Strategy. *Strategic report commissioned by the City of Wenatchee.* 14pps.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental Health Risks and Housing Values: Evidence From 1,600 Toxic Plant Openings and Closings." *The American Economic Review* 105 (2): 678-709.

Dale, Larry, James C. Murdoch, Mark A. Thayer, and Paul A. Waddell. 1999. "Do Property Values Rebound from Environmental Stigmas? Evidence from Dallas." *Land Economics* 75 (7): 311-326.

Davenport, J. R., and F. J. Peryea. 1991. "Phosphate Fertilizers Influence Leaching of Lead and Arsenic in a Soil Contaminated with Lead Arsenate." *Water, Air, and Soil Pollution* 57 (1): 101-110.

Defoe, Phillip P., Ganga M. Hettiarachchi, Christopher Benedict, and Sabine Martin. 2014. "Safety of Gardening on Lead-and Arsenic-Contaminated Urban Brownfields." *Journal of Environmental Quality* 43 (6): 2064-2078.

Democratic Presidential Primary Debate. CNN. Flint, MI. March 7, 2016. 8:00 p.m. EST Statement by Secretary of State Hilary Clinton. Full transcript available at: http://cnnpressroom.blogs.cnn.com/2016/03/06/final-rush-transcriptcnndemocratic-presidential-primary-debate-flint-mi/

Elfving, Don C., Kenneth R. Wilson, Joseph G. Ebel, Kerry L. Manzell, Walter H. Gutenmann, and Donald J. Lisk. 1994. "Migration of Lead and Arsenic in Old Orchard Soils in the Georgian Bay Region of Ontario." *Chemosphere* 29 (2): 407-413.

Environmental Protection Agency (EPA). “Case Summary: ASARCO 2009 Bankruptcy Settlement.” *Enforcement* n.d. Accessed April 23, 2017. https://www.epa.gov/enforcement/case-summary-asarco-2009-bankruptcy-settlement#general

Examining Federal Administration of the Safe Drinking Water Act in Flint, MI: Hearing before the Full House Committee on Government Oversight and Reform. 114th Congress. 1. February 3, 2016. 11:47a.m. EST. Testimony of Mr. Joel Beauvais, Acting Deputy Assistant Administrator, Office of Water, Environmental Protection Agency.

Gamper-Rabindran, Shanti and Christopher Timmins. 2013. "Does Cleanup of Hazardous Waste Sites Raise Housing Values? Evidence of Spatially Localized Benefits." *Journal of Environmental Economics and Management* 65 (3): 345-360.

Guignet, Dennis. 2013 "What do Property Values Really Tell Us?: A Hedonic Study of Underground Storage Tanks." *Land Economics* 89 (2): 211-226.

Haninger, Kevin, Lala Ma, and Christopher Timmins. 2017. "The Value of Brownfield Remediation." *Journal of the Association of Environmental and Resource Economists* 4 (1): 197-241.

Henry, Heather, Marisa F. Naujokas, Chammi Attanayake, Nicholas T. Basta, Zhongqi Cheng, Ganga M. Hettiarachchi, Mark Maddaloni, Christopher Schadt, and Kirk G. Scheckel. 2015. "Bioavailability-Based In Situ Remediation to Meet Future Lead (Pb) Standards in Urban Soils and Gardens." *Environmental Science & Technology* 49 (15): 8948-8958.

Hood, Ernie.2006. "The Apple Bites Back: Claiming Old Orchards for Residential Development." *Environmental Health Perspectives* 114 (8): A470.

Hsieh, Hsiu-Fang and Sarah E. Shannon. 2005. "Three Approaches to Qualitative Content Analysis." *Qualitative Health Research* 15 (5): 1277-1288.

Jenkins-Smith, Hank C., Carol L. Silva, Robert P. Berrens, and Alok Bohara. 2002. "Information Disclosure Requirements and the Effect of Soil Contamination on Property Values." *Journal of Environmental Planning and Management* 45 (3): 323-339.

Kiel, Katherine A. 1995. "Measuring the Impact of the Discovery and Cleaning of Identified Hazardous Waste Sites on House Values." *Land Economics* 71 (4): 428-435.

Kling, Barry, Frank Collins, and Mark Marquis. "Take Lead and Public Health Seriously." *Wenatchee World* (Wenatchee, WA), October 9, 2005. Accessed December 10, 2015. http://www.wenatcheeworld.com/news/2005/oct/09/take-lead-andpublichealth-seriously/

Kohlhase, Janet E. 1991. "The Impact of Toxic Waste Sites on Housing Values." *Journal of Urban Economics* 30 (1): 1-26.

Kovarik, William. 2005. "Ethyl-Leaded Gasoline: How a Classic Occupational Disease Became an International Public Health Disaster." *International Journal of Occupational and Environmental Health* 11 (4): 384-397.

Lancaster, Kelvin J. 1966. "A New Approach to Consumer Theory." *Journal of Political Economy* 74 (2): 132-157.

Lanphear, Bruce P., Richard Hornung, Jane Khoury, Kimberly Yolton, Peter Baghurst, David C. Bellinger, Richard L. Canfield et al. 2005. ”Low-Level Environmental Lead Exposure and Children’s Intellectual Function: An International Pooled Analysis." *Environmental Health Perspectives* 113 (7): 894.

Le Goffe, P. 2000. “Hedonic Pricing of Agriculture and Forestry Externalities.” *Environmental and Resource Economics* 15(4): 397-401.

Li, Chia-Nung, Chien-Wen Lo, Wei-Chiang Su, and Tsung-Yu Lai. 2015. "A Study on Soil and Groundwater Pollution Remediation of the Surrounding Real Estate Prices and Tax Revenue Impact." *Sustainability* 7 (11): 14618-14630.

McCluskey, Jill J., and Gordon C. Rausser. 2001. "Estimation of Perceived Risk and its Effect on Property Values." *Land Economics* 77 (1): 42-55.

McCluskey, Jill J. and Gordon C. Rausser. 2003. “Hazardous Waste Sites and Housing Appreciation Rates.” *Journal of Environmental Economics and Management 45* (2): 166-176.

Mielke, Howard W., and Patrick L. Reagan. 1998. "Soil is an Important Pathway of Human Lead Exposure." *Environmental Health Perspectives* 106 (1): 217.

Mihaescu, Oana, and Rainer vom Hofe. 2012. "The Impact of Brownfields on Residential Property Values in Cincinnati, Ohio: A Spatial Hedonic Approach." *Journal of Regional Analysis & Policy* 42 (3): 223.

Model Toxics Control Act of 1989, RCW 70.105D. Accessed April 23, 2017. http://app.leg.wa.gov/rcw/default.aspx?cite=70.105D

Muennig, Peter. 2009. "The Social Costs of Childhood Lead Exposure in the Post–Lead Regulation Era." *Archives of Pediatrics & Adolescent Medicine* 163 (9): 844-849.

Needleman, Herbert L., Alan Schell, David C. Bellinger, Alan Leviton, and Elizabeth N. Allred. 1990. ”The Long-Term Effects of Exposure to Low Doses of Lead in Childhood: An 11-Year Follow-up Report." *New England Journal of Medicine* 322 (2): 83-88.

Needleman, Herbert L. 1991. "Childhood Lead Poisoning: A Disease for the History Texts." *American Journal of Public Health* 81 (6): 685-687.

Palmquist, Raymond B. 1988. "Welfare Measurement for Environmental Improvements Using the Hedonic Model: The Case of Nonparametric Marginal Prices." *Journal of Environmental Economics and Management* 15 (3): 297-312.

Palmquist, Raymond B., and V. Kerry Smith. 2002. "The Use of Hedonic Property Value Techniques for Policy and Litigation." *The International Yearbook of Environmental and Resource Economics 2002/2003* (VI): 115-64.

Parmeter, Christopher F., and Jaren C. Pope. 2009. "Quasi-Experiments and Hedonic Property Value Methods." http://dx.doi.org/10.2139/ssrn.1283705

Peryea, F. J., and T. L. Creger. 1994. "Vertical Distribution of Lead and Arsenic in Soils Contaminated with Lead Arsenate Pesticide Residues." *Water, Air, and Soil Pollution* 78 (3-4): 297-306.

Peryea, Francis J. 1998. "Historical Use of Lead Arsenate Insecticides, Resulting Soil Contamination and Implications for Soil Remediation." In *16th World Congress of Soil Science, Montpellier, France*. 20-26.

Peters, Robert W., and Linda Shem. 1992. "Adsorption/Desorption Characteristics of Lead on Various Types of Soil." *Environmental Progress* 11 (3): 234-240.

Port of Chelan County. “Large Employers List.” 2015. Accessed February 17, 2016. http://www.portofchelancounty.com/home/showdocument?id=530

Rabin, Richard. 1989. "Warnings Unheeded: A History of Child Lead Poisoning. "*American Journal of Public Health* 79 (2): 1668-1674.

Rosen, Sherwin. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *Journal of Political Economy* 82 (1): 34-55.

Ruby, M. V., R. Schoof, W. Brattin, M. Goldade, G. Post, M. Harnois, D. E. Mosby et al. 1999. "Advances in Evaluating the Oral Bioavailability of Inorganics in Soil for Use in Human Health Risk Assessment." *Environmental Science & Technology* 33 (21): 3697-3705.

Sadiq, Muhammad. 1997. "Arsenic Chemistry in Soils: An Overview of Thermodynamic Predictions and Field Observations." *Water, Air, and Soil Pollution* 93 (1-4): 117-136.

Schick, Tony and Courtney Flatt. Oregon Public Broadcasting *Contaminated Soil Lingers Where Apples Once Grew*. October 12, 2015. Accessed February 4, 2016. http://www.opb.org/news/article/contaminated-soil-lingers-where-apples-once-grew/

Schooley, Therese, Michael Weaver, Donald Mullins, and Matthew Eick. 2009. "The History of Lead Arsenate Use in Apple Production: Comparison of its Impact in Virginia with Other states." *Journal of Pesticide Safety Education* (10): 22-53.

Segerson, Kathleen. 1994. "Property Transfers and Environmental Pollution: Incentive Effects of Alternative Policies." *Land Economics* 70 (3): 261-272.

Shepard, Harold Henry. *The Chemistry and Action of Insecticides*. (New York: McGraw Hill, 1951).

Slovic, Paul. 1987. "Perception of Risk." *Science* 236 (4799): 280-285.

Slovic, Paul. *The Pperception of Risk. Risk, Society, and Policy Series.* (London: Earthscan, 2000).

Starr, C. 1969. "Social Benefit Versus Technological Risk." *Science* 165 (3899): 1232-1238

State of Washington Office of Superintendent of Public Instruction (OSPI). "K-12 Data and Reports." 2013. Accessed February 17, 2016. http://www.k12.wa.us/default.aspx

Steigmeyer, Rick. "Lead: It's a Fact of NCW Life." *Wenatchee World* (Wenatchee, WA) June 7, 2001.

Taylor, Laura O., Daniel J. Phaneuf, and Xiangping Liu. 2016."Disentangling Property Value Impacts of Environmental Contamination from Locally Undesirable Land Uses: Implications for Measuring Post-Cleanup Stigma." *Journal of Urban Economics* 93: 85-98.

Tobey, James A., and Henri Smets. 1996. "The Polluter-Pays Principle in the Context of Agriculture and the Environment." *The World Economy* 19 (1): 63-87.

Tversky, Amos and Daniel Kahneman. 1973. "Availability: A Heuristic for Judging Frequency and Probability." *Cognitive Psychology* 5 (2): 207-232.

Tyler, A. 1988."How Actuaries and Underwriters Look at Risk." *European Heart Journal* 9 (suppl_G): 31-35.

United States Census. “State & County QuickFacts” Last Revised December 2, 2015. Accessed February 17, 2016. http://quickfacts.census.gov/qfd/states/53/5377105.html

United States Department of Agriculture (USDA). “2012 Census of Agriculture – County Data: Table 8. Farms, Land in Farms, Value of Land and Buildings, and Land Use: 2012 and 2007.” 2012. Accessed February 17, 2016. http://www.agcensus.usda.gov/Publications/2012/Full_Report/Volume_1,_Chatr_2_County_Level/Washington/st53_2_008_008.pdf

United States Department of Agriculture - Natural Resources Conservation Service (USDA-NRCS). “Development of Non-Federal Rural Land 2007.” 2007 http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/technical/nra/nri/results/?cid=stelprdb1083197. Accessed November 19, 2015.

United States Department of Agriculture - Natural Resources Conservation Service (USDA-NRCS). “Web Soil Survey.” *Soil Survey Staff.* Last modified Dec 6, 2013. Accessed February 18, 2016. http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm

United States Department of Agriculture - Natural Resources Conservation Service (USDA-NRCS). “Official Soil Series Descriptions.” *Soil Survey Staff.* Accessed February 18 2016. http://soils.usda.gov/technical/classification/osd/index.html

Veneman, P. L. M., J. R. Murray, and J. H. Baker. 1983. "Spatial Distribution of Pesticide Residues in a Former Apple Orchard." *Journal of Environmental Quality* 12 (1): 101-104.

Wakefield, Sarah E.L. and Susan J. Elliot. 2003. “Constructing the News: The Role of Local Newspapers in Environmental Risk Communication” *The Professional Geographer* 55 (2): 216-226.

Walsh, Patrick, and Preston Mui. 2017. "Contaminated Sites and Information in Hedonic Models: An Analysis of a NJ Property Disclosure Law." *Resource and Energy Economics* 50: 1-14.

Warner, Tracy. “Get the Lead Out? Why?” *Wenatchee World* (Wenatchee, WA) September 29, 2005. Accessed December 10, 2015. http://www.wenatcheeworld.com/news/2005/sep/29/get-the-lead-out-why/

Washington State Conservation Commission (WSCC). “Coordinated Resource Management.” n.d. Accessed August 30, 2017. http://scc.wa.gov/coordinated-resource-management/

Washington State Department of Ecology (ECY). “Tacoma Smelter Plume.” *Toxics Cleanup Program.* 2011. Accessed April 23, 2017. http://www.ecy.wa.gov/programs/tcp/sites_brochure/tacoma_smelter/2011/ts-hp.htm

Washington State Department of Ecology (ECY). “Former Orchard Lands.” *Toxics Cleanup Program.* 2012. Accessed February 4, 2016. http://www.ecy.wa.gov/programs/tcp/area_wide/2012/former-orch-lands.html

Washington State Department of Ecology (ECY). “Area-Wide Soil Contamination Project.” *Toxics Cleanup Program.* n.d. Accessed April 23, 2017. http://www.ecy.wa.gov/programs/tcp/area_wide/AW/toolbox_chap1.html

Weber, Eric and Kris Hendrickson. “Technical Memorandum: Arsenic and Lead Mobility in Area-Wide Contamination Impacted Soil.” *From Landau Associates to Washington Department of Ecology.* September 14, 200 http://www.ecy.wa.gov/programs/tcp/SAB/SAB_mtg_info/mtg_061211/As%20&%20Pb%20Mobility_TM.pdf

Weber, Robert Philip. *Basic Content Analysis*. No. 49. (Newbury Park: Sage, 1990).

Wenatchee School District. (WSD) “District Attendance Areas.” Student Services Policy 3130. 2015. Accessed November 14, 2017. https://campussuite-storage.s3.amazonaws.com/prod/3059/7610d33a-0c90-11e6-b537-22000bd8490f/609570/d9594f17-6a02-11e6-b388-22000bd8490f/file/1Policy_3130.pdf

Welch, Alan H., Michael S. Lico, and Jennifer L. Hughes. 1988. "Arsenic in Ground Water of the Western United States." *Ground Water* 26 (3): 333-347.

World Health Organization (WHO). “Lead Poisoning and Health.” *Media Centre.* Updated August 2015. Accessed February 4, 2016. http://www.who.int/mediacentre/factsheets/fs379/en/

Wolz, Sarah, Richard A. Fenske, Nancy J. Simcox, Gary Palcisko, and John C. Kissel. 2003. "Residential Arsenic and Lead Levels in an Agricultural Community with a History of Lead Arsenate Use." *Environmental Research* 93 (3): 293-300.

Zabel, Jeffrey. 2007. "The Impact of Imperfect Information on the Transactions of Contaminated Properties." *National Center for Environmental Economics, US Environmental Protection Agency.* Working Paper No. 07-03.

Zierold, Kristina M., Lynda Knobeloch, and Henry Anderson. 2004. "Prevalence of Chronic Diseases in Adults Exposed to Arsenic-Contaminated Drinking Water." *American Journal of Public Health* 94 (11): 1936-1937.

Zimdahl, Robert L., and Rodney K. Skogerboe. 1977. "Behavior of Lead in Soil." *Environmental Science & Technology* 11 (13): 1202-1207.

Appendixes

A. Variable Definitions

Name in Stata	Definition
Sales Variables	
lnrealprice	dependent variable - log of price adjusted for inflation to 2015 dollars
saledate	date home was sold
quarteryear	year and quarter of sale date i.e. 1st quarter of 2008
Housing Variables	
age	age of home
age2	quadratic age term
mainfloorsqft	area of main floor of home in square feet
bedrooms	number of bedrooms
bathrooms	number of bathrooms
garagearea	area of garage in square feet
Neighborhood Variables	
middleschoolzone	which middle school home is associated with
eleschoolzone	which elementary school home is associated with
blockid	U.S. Census block ID
block_grp	U.S. Census block group number
Elementary School Cleanup Treatment Variables	
announce_e	announcement date, elementary
list_e	listing date, elementary
start_e	start of cleanup, elementary
end_e	end of cleanup, elementary
delist_e	delisting, elementary
genclean_e	general cleanup, elementary
genclean_m	general cleanup, middle school
days_anna	days from cleanup announcement to sale date
threemonth_anne	3 months from cleanup announcement
half_anne	6 months from cleanup announcement
ninemonth_anne	9 months from cleanup announcement
year_anne	12 months from cleanup announcement
yearhalf_anne	18 months from cleanup announcement
twoyear_anne	24 months from cleanup announcement
twohalfyear_anne	30 months from cleanup announcement
threeyear_anne	36 months from cleanup announcement
days_liste	days from cleanup announcement to listing date
threemonth_liste	3 months from cleanup announcement
half_liste	6 months from listing as a hazardous site
ninemonth_liste	9 months from cleanup announcement
year_liste	12 months from listing a hazardous site
yearhalf_liste	18 months from listing a hazardous site

twoyear_liste	24 months from listing a hazardous site
twohalfyear_liste	30 months from listing a hazardous site
threeyear_liste	36 months from listing a hazardous site
days_starte	days from start of cleanup to sale date
threemonth_anne	3 months from start of cleanup
half_starte	6 months from start of cleanup
ninemonth_anne	9 months from start of cleanup
year_starte	12 months from start of cleanup
yearhalf_starte	18 months from start of cleanup
twoyear_starte	24 months from start of cleanup
twohalfyear_starte	30 months from start of cleanup
threeyear_starte	36 months from start of cleanup
days_ende	days from end of cleanup to sale date
threemonth_ende	3 months from end of cleanup
half_ende	6 months from end of cleanup
ninemonth_ende	9 months from end of cleanup
year_ende	12 months from end of cleanup
yearhalf_ende	18 months from end of cleanup
twoyear_ende	24 months from end of cleanup
twohalfyear_ende	30 months from end of cleanup
threeyear_ende	36 months from end of cleanup
day_deliste	days from delisting to sale date
threemonth_deliste	3 months from delisting
ninemonth_deliste	9 months from delisting
half_deliste	6 months from delisting
year_deliste	12 months from delisting
yearhalf_deliste	18 months from delisting
twoyear_deliste	24 months from delisting
twohalfyear_deliste	30 months from delisting
threeyear_deliste	36 months from delisting

Middle School Cleanup Treatment Variables

announce_m	announcement date, middle school
list_m	listing date, middle school
start_m	start of cleanup, middle school
end_m	end of cleanup, middle school
delist_m	delisting, middle school
days_annm	days from cleanup announcement to sale date
threemonth_annm	3 months from cleanup announcement
half_annm	9 months from cleanup announcement
ninemonth_annm	3 months from cleanup announcement
year_annm	12 months from cleanup announcement
yearhalf_annm	18 months from cleanup announcement
twoyear_annm	24 months from cleanup announcement
twohalfyear_annm	30 months from cleanup announcement
threeyear_annm	36 months from cleanup announcement
days_listm	days from cleanup announcement to listing date
threemonth_listm	3 months from listing as a hazardous site
half_listm	6 months from listing as a hazardous site
ninemonth_listm	9 months from listing as a hazardous site

year_listm	12 months from listing a hazardous site
yearhalf_listm	18 months from listing a hazardous site
twoyear_listm	24 months from listing a hazardous site
twohalfyear_listm	30 months from listing a hazardous site
threeyear_listm	36 months from listing a hazardous site
days_startm	days from start of cleanup to sale date
threemonth_startm	3 months from start of cleanup
half_startm	6 months from start of cleanup
ninemonth_startm	9 months from start of cleanup
year_startm	12 months from start of cleanup
yearhalf_startm	18 months from start of cleanup
twoyear_startm	24 months from start of cleanup
twohalfyear_startm	30 months from start of cleanup
threeyear_startm	36 months from start of cleanup
days_endm	days from end of cleanup to sale date
half_endm	6 months from end of cleanup
year_endm	12 months from end of cleanup
yearhalf_endm	18 months from end of cleanup
twoyear_endm	24 months from end of cleanup
twohalfyear_endm	30 months from end of cleanup
threeyear_endm	36 months from end of cleanup
days_delistm	days from delisting to sale date
threemonth_delistm	3 months from delisting
half_delistm	6 months from delisting
ninemonth_delistm	9 months from delisting
year_delistm	12 months from delisting
yearhalf_delistm	18 months from delisting
twoyear_delistm	24 months from delisting
twohalfyear_delistm	30 months from delisting
threeyear_delistm	36 months from delisting

Media Treatment Variables

media_30	30 days from publication of relevant article
media_60	60 days from publication of relevant article
media_90	90 days from publication of relevant article

B. Regression Analysis Code (Stata)

```
*elem_all_events

reg lnrealprice threemnth_anne threemonth_liste threemonth_starte threemonth_ende threemnth_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel

reg lnrealprice half_anne half_liste half_starte half_ende half_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel

reg lnrealprice ninemonth_anne ninemonth_liste ninemonth_starte ninemonth_ende ninemonth_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel

reg lnrealprice year_anne year_liste year_starte year_ende year_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice yearhalf_anne yearhalf_liste yearhalf_starte yearhalf_ende yearhalf_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice twoyear_anne twoyear_liste twoyear_starte twoyear_ende twoyear_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
```

```
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice twohalfyear_anne twohalfyear_liste twohalfyear_starte twohalfyear_ende twohalfyear_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice threeyear_anne threeyear_liste threeyear_starte threeyear_ende threeyear_deliste mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\elem1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append


*middle_all_events

reg lnrealprice threemonth_annm threemonth_listm threemonth_startm threemonth_endm threemonth_delistm mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel

reg lnrealprice half_annm half_listm half_startm half_endm half_delistm mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel

reg lnrealprice ninemonth_annm ninemonth_listm ninemonth_startm ninemonth_endm ninemonth_delistm mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp) excel
```

```
reg lnrealprice year_annm year_listm year_startm year_endm year_delistm mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp  if middleschoolzone!="0" &
mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice yearhalf_annm yearhalf_listm yearhalf_startm yearhalf_endm yearhalf_delistm
mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice twoyear_annm twoyear_listm twoyear_startm twoyear_endm twoyear_delistm
mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice twohalfyear_annm twohalfyear_listm twohalfyear_startm twohalfyear_endm
twohalfyear_delistm mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice threeyear_annm threeyear_listm threeyear_startm threeyear_endm
threeyear_delistm mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_all", drop(mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp) excel append



foreach event of varlist threemnth_anne threemonth_liste threemonth_starte
threemonth_ende threemnth_deliste half_anne half_liste half_starte half_ende half_deliste
ninemonth_anne ninemonth_liste ninemonth_starte ninemonth_ende ninemonth_deliste
year_anne year_liste year_starte year_ende year_deliste yearhalf_anne yearhalf_liste
yearhalf_starte yearhalf_ende yearhalf_deliste twoyear_anne twoyear_liste twoyear_starte
twoyear_ende twoyear_deliste twohalfyear_anne twohalfyear_liste twohalfyear_starte
```

```
twohalfyear_ende twohalfyear_deliste threeyear_anne threeyear_liste threeyear_starte
threeyear_ende threeyear_deliste {

reg lnrealprice `event' mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
eleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
eleschoolzone) robust

outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\elem1_st_single", keep(`event') excel append
}

*middle_single_event

foreach event of varlist threemonth_annm threemonth_listm threemonth_startm
threemonth_endm threemonth_delistm half_annm half_listm half_startm half_endm
half_delistm ninemonth_annm ninemonth_listm ninemonth_startm ninemonth_endm
ninemonth_delistm year_annm year_listm year_startm year_endm year_delistm yearhalf_annm
yearhalf_listm yearhalf_startm yearhalf_endm yearhalf_delistm twoyear_annm twoyear_listm
twoyear_startm twoyear_endm twoyear_delistm twohalfyear_annm twohalfyear_listm
twohalfyear_startm twohalfyear_endm twohalfyear_delistm threeyear_annm threeyear_listm
threeyear_startm threeyear_endm threeyear_deliste {

reg lnrealprice `event' mainfloorsqft bedrooms age age2 garagearea i.quarteryear i.block_grp  if
middleschoolzone!="0" & mainfloorsqft >600 & mainfloorsqft <2720 & bedrooms>0,cluster(
middleschoolzone) robust

outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead Arsenate\Results\_July
regression - CLUSTERED Toni\middle1_st_single", keep(`event') excel append

*elem rings
reg lnrealprice half_anne nine_monthanne year_anne yearhalf_anne twoyear_anne
twohalfyear_anne threeyear_anne half_liste ninemonth_liste year_liste yearhalf_liste
twoyear_liste twohalfyear_liste threeyear_liste half_starte ninemonth_starte year_starte
yearhalf_starte twoyear_starte twohalfyear_starte threeyear_starte half_ende
ninemonth_ende year_ende yearhalf_ende twoyear_ende twohalfyear_ende threeyear_ende
half_deliste ninemonth_deliste year_deliste yearhalf_deliste twoyear_deliste
twohalfyear_deliste threeyear_deliste mainfloorsqft bedrooms age age2 garagearea
i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel replace

reg lnrealprice half_anne nine_monthanne year_anne yearhalf_anne twoyear_anne
twohalfyear_anne threeyear_anne mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
```

```
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_liste ninemonth_liste year_liste yearhalf_liste twoyear_liste
twohalfyear_liste threeyear_liste  mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_starte ninemonth_starte year_starte yearhalf_starte twoyear_starte
twohalfyear_starte threeyear_starte mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_ende ninemonth_ende year_ende yearhalf_ende twoyear_ende
twohalfyear_ende threeyear_ende mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_deliste ninemonth_deliste year_deliste yearhalf_deliste twoyear_deliste
twohalfyear_deliste threeyear_deliste mainfloorsqft bedrooms age age2 garagearea
i.quarteryear i.block_grp  if eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster( eleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\elem_rings_sum" if
eleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3052 & bedrooms>0, sum (log)
keep(mainfloorsqft bedrooms age garagearea) excel replace



*mid
reg lnrealprice half_annm ninemonth_annm year_annm yearhalf_annm twoyear_annm
twohalfyear_annm threeyear_annm half_listm ninemonth_listm year_listm yearhalf_listm
twoyear_listm twohalfyear_listm threeyear_listm half_startm ninemonth_startm year_startm
```

```
yearhalf_startm twoyear_startm twohalfyear_startm threeyear_startm half_endm
ninemonth_endm year_endm yearhalf_endm twoyear_endm twohalfyear_endm
threeyear_endm half_delistm ninemonth_delistm year_delistm yearhalf_delistm
twoyear_delistm twohalfyear_delistm threeyear_delistm mainfloorsqft bedrooms age age2
garagearea i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 &
mainfloorsqft <3050 & bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel replace

reg lnrealprice half_annm ninemonth_annm year_annm yearhalf_annm twoyear_annm
twohalfyear_annm threeyear_annm mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 &
bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_listm ninemonth_listm year_listm yearhalf_listm twoyear_listm
twohalfyear_listm threeyear_listm mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 &
bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_startm ninemonth_startm year_startm yearhalf_startm twoyear_startm
twohalfyear_startm threeyear_startm mainfloorsqft bedrooms age age2 garagearea
i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 &
bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_endm ninemonth_endm year_endm yearhalf_endm twoyear_endm
twohalfyear_endm threeyear_endm mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 &
bedrooms>0,cluster( middleschoolzone) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice half_delistm ninemonth_delistm year_delistm yearhalf_delistm twoyear_delistm
twohalfyear_delistm threeyear_delistm mainfloorsqft bedrooms age age2 garagearea
i.quarteryear i.block_grp  if middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 &
bedrooms>0,cluster( middleschoolzone) robust
```

```
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\middle_rings_sum" if
middleschoolzone!="0" & mainfloorsqft >0 & mainfloorsqft <3050 & bedrooms>0, sum (log)
keep(mainfloorsqft bedrooms age garagearea) excel replace


*media rings
reg lnrealprice media_30 media_60 media_90 mainfloorsqft bedrooms age age2 garagearea
i.quarteryear i.block_grp if city==1 & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster(block_grp) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\media_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel replace

reg lnrealprice media_30 mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if city==1  & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster(block_grp) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\media_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice media_60 mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if city==1  & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster(block_grp) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\media_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append

reg lnrealprice media_90 mainfloorsqft bedrooms age age2 garagearea i.quarteryear
i.block_grp  if city==1 & mainfloorsqft >0 & mainfloorsqft <3052 &
bedrooms>0,cluster(block_grp) robust
outreg2 using "C:\Users\sipict\Google Drive\Economic Impacts of Lead
Arsenate\Results\November results Toni\Final draft results\media_rings", drop(mainfloorsqft
bedrooms age age2 garagearea i.quarteryear i.block_grp) excel append
```

C. Elementary Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.0424	-0.0590	-0.0687	-0.0951	-0.105	-0.0977	-0.0979
	(0.0597)	(0.0676)	(0.0556)	(0.0538)	(0.0575)	(0.0549)	(0.0622)
Listed	0.0110	-0.00811	0.0772	0.0636	0.0271	0.0120	-0.0149
	(0.0406)	(0.0408)	(0.0484)	(0.0399)	(0.0403)	(0.0479)	(0.0358)
Started	-0.00945	-0.0549	-0.0555	-0.0720	0.0245	0.0444	0.131*
	(0.0971)	(0.0542)	(0.0740)	(0.0579)	(0.0484)	(0.0521)	(0.0626)
Ended	0.0515	0.0791*	0.0530	0.0502	0.00680	-0.00726	-0.0355
	(0.0620)	(0.0353)	(0.0545)	(0.0513)	(0.0557)	(0.0845)	(0.0992)
Delisted	0.0539**	0.0467**	0.0308	-0.0716	-0.0378	-0.0520	-0.0653
	(0.0198)	(0.0190)	(0.0262)	(0.122)	(0.103)	(0.0917)	(0.0915)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.309	0.310	0.310	0.310	0.310	0.311

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

D. Middle School Results - Functional Form A

Variables	0-6 months	0-9 months	0-1 years	0-1.5 years	0-2 years	0-2.5 years	0-3 years
Announced	-0.0345	-0.0938	-0.0730	-0.0710	-0.0872	-0.0780	-0.0819
	(0.0520)	(0.0577)	(0.0640)	(0.0775)	(0.0788)	(0.0780)	(0.0740)
Listed	0.0247	0.00317	-0.0111	0.0165	-0.0176	-0.00373	0.00994
	(0.0312)	(0.0324)	(0.0241)	(0.0133)	(0.0187)	(0.0160)	(0.0121)
Started	-0.290	-0.162	-0.107	-0.0704	-0.0492	-0.0276	-0.0643
	(0.265)	(0.127)	(0.0947)	(0.0571)	(0.0392)	(0.0277)	(0.0221)
Ended	0.0797	0.125	0.0610	0.0600	0.0489	-0.0396	-0.0114
	(0.0815)	(0.0971)	(0.0828)	(0.0364)	(0.0275)	(0.0415)	(0.0505)
Delisted	-0.00946	0.00791	-0.00472	0.0208	0.0136	0.0390	0.0432
	(0.0168)	(0.00839)	(0.0210)	(0.0223)	(0.0465)	(0.0717)	(0.0732)
House Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980	9,980	9,980
R-squared	0.311	0.310	0.310	0.310	0.310	0.310	0.310

Note: Robust standard errors in parentheses, clustered on middle school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

E. Full Regression Results - Functional Form B

Variables		ELEM	MID
Announced			
	0-6 months	-0.149*	-0.0482
		(0.0729)	(0.0471)
	6-9 months	-0.101	-0.145
		(0.0706)	(0.0575)
	9-12 months	-0.0409	-0.000340
		(0.0519)	(0.101)
	1-1.5 years	-0.0987	-0.0764
		(0.0538)	(0.113)
	1.5-2 years	-0.119*	-0.143
		(0.0547)	(0.0769)
	2-2.5 years	-0.0756	-0.0457
		(0.0615)	(0.0865)
	2.5-3 years	-0.0515	-0.0752
		(0.0784)	(0.0528)
Listed			
	0-6 months	-0.0289	0.0108
		(0.0265)	(0.0416)
	6-9 months	-	-0.0709
		-	(0.0289)
	9-12 months	0.0796	-0.0628
		(0.132)	(0.0308)
	1-1.5 years	-0.0733	0.0749
		(0.0452)	(0.0500)
	1.5-2 years	-0.114*	-0.0574**
		(0.0514)	(0.0116)
	2-2.5 years	-0.0820	0.0485
		(0.0630)	(0.0214)
	2.5-3 years	-0.0110	-0.0807**
		(0.0380)	(0.0122)
Started			
	0-6 months	-0.0673	-0.0451
		(0.133)	(0.125)
	6-9 months	-0.0345	0.369
		(0.0759)	(0.285)
	9-12 months	0.128**	-0.0532
		(0.0505)	(0.116)

	1-1.5 years	0.0799	-0.0193
		(0.0457)	(0.121)
	1.5-2 years	0.261**	0.0366
		(0.0910)	(0.0606)
	2-2.5 years	0.225***	-0.00246
		(0.0482)	(0.00564)
	2.5-3 years	0.286***	-0.153**
		(0.0343)	(0.0280)
Ended			
	0-6 months	0.279	0.135*
		(0.313)	(0.0356)
	6-9 months	0.177	0.354***
		(0.266)	(0.0299)
	9-12 months	0.0882	0.0290
		(0.111)	(0.0197)
	1-1.5 years	-0.0191	0.166**
		(0.134)	(0.0205)
	1.5-2 years	-0.0846	0.0315
		(0.143)	(0.0999)
	2-2.5 years	-0.141	-0.399
		(0.0947)	(0.245)
	2.5-3 years	-0.0537*	0.0680
		(0.0259)	(0.144)
Delisted			
	0-6 months	0.0491**	-0.0119
		(0.0169)	(0.0149)
	6-9 months	0.0941	0.0606
		(0.103)	(0.0285)
	9-12 months	-0.0728	-0.0388
		(0.0983)	(0.0615)
	1-1.5 years	-0.317	0.00263
		(0.368)	(0.0446)
	1.5-2 years	-0.175	-0.172
		(0.235)	(0.0947)
	2-2.5 years	-0.121	-0.164**
		(0.100)	(0.0256)
	2.5-3 years	0.0141	-0.0102
		(0.144)	(0.0401)
House Characteristics		Yes	Yes
Census Block Group FE		Yes	Yes
Quarter-by-Year FE		Yes	Yes

Observations	10,080	9,980
R-squared	0.318	0.316

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

F. Elementary Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.0445	0.0160	0.0153	0.0153	0.0521**
	(0.0588)	(0.0342)	(0.0747)	(0.0747)	(0.0183)
6-9 months	-0.0407	-0.0291	-0.0670	-0.0670	0.0783
	(0.0627)	(0.0587)	(0.0528)	(0.0528)	(0.0895)
9-12 months	-0.0799	0.179	0.00366	0.00366	-0.0525
	(0.0764)	(0.153)	(0.0487)	(0.0487)	(0.0806)
1-1.5 years	-0.130*	-0.0209	0.00667	0.00667	-0.177
	(0.0580)	(0.0287)	(0.0355)	(0.0355)	(0.236)
1.5-2 years	-0.135*	-0.0679	0.156*	0.156*	0.0290
	(0.0590)	(0.0442)	(0.0674)	(0.0674)	(0.0643)
2-2.5 years	-0.0784	-0.0807	0.0354	0.0354	-0.0562
	(0.0643)	(0.0605)	(0.0882)	(0.0882)	(0.0424)
2.5-3 years	-0.0506	-0.0326	0.161	0.161	0.00214
	(0.0796)	(0.0470)	(0.103)	(0.103)	(0.0306)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,080	10,080	10,080	10,080	10,080
R-squared	0.309	0.311	0.311	0.309	0.310

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

G. Middle School Results - Functional Form C

Variables	Announced	Listed	Started	Ended	Delisted
0-6 months	-0.0500	0.0218	-0.292	0.0844	-0.00387
	(0.0650)	(0.0344)	(0.266)	(0.0821)	(0.0116)
6-9 months	-0.209*	-0.0353	-0.00564	0.187	0.0532
	(0.0698)	(0.0287)	(0.0470)	(0.116)	(0.0329)
9-12 months	-0.00709	-0.0458**	0.0173	-0.133	-0.0236
	(0.102)	(0.00739)	(0.0321)	(0.0488)	(0.0648)
1-1.5 years	-0.0733	0.0179	0.0178	0.0683*	0.122
	(0.113)	(0.0616)	(0.0321)	(0.0192)	(0.0573)
1.5-2 years	-0.141	-0.159**	-0.00246	0.0140	0.0503
	(0.0760)	(0.0171)	(0.0262)	(0.0251)	(0.112)
2-2.5 years	-0.0428	0.0148	0.0273	-0.217	-0.0152
	(0.0860)	(0.0512)	(0.0439)	(0.157)	(0.0233)
2.5-3 years	-0.0727	-0.166*	-0.156*	0.0381	0.0688**
	(0.0533)	(0.0552)	(0.0444)	(0.0322)	(0.0137)
House Characteristics	Yes	Yes	Yes	Yes	Yes
Census Block Group FE	Yes	Yes	Yes	Yes	Yes
Quarter-by-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,980	9,980	9,980	9,980	9,980
R-squared	0.310	0.310	0.312	0.311	0.309

Note: Robust standard errors in parentheses, clustered on elementary school zone level. P-values: *** p<0.01, ** p<0.05, * p<0.1

H. Content Analysis Code Book (Generated by Atlas.TI)

- **Blood levels = elevated**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> States that NCW children have elevated blood lead levels

- **Blood levels = hispanic**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Claims that the majority of children with elevated levels are Hispanic, and that these children are exposed in other ways, i.e. home remedies. This is significant in that it could be used to redirect blame from orchards as well as to argue against the school soils being hazardous.

- **Cost**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Relates to the cost/burden of cleanup

- **Cost = local**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> WSD (locals) will pay the cost.

- **Cost = state**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> ECY (state) will pay costs.

- **ECY = Agenda**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Claims ECY is motivated by an agenda or ulterior motive

- **ECY = Protection**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Demonstrates that ECY is motivated by a need to protect the public

---

- **Expert**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Quotation of an "expert:" medical doctor, agency representative, Task Force member, scientific study, etc. Important for co-occurrence analysis.

- **Hazard = no**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Asserts that lead arsenate soil contamination and/or lead in general pose no danger to health

---

- **Hazard = yes**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Asserts that lead arsenate soil contamination and/or lead in general pose a danger to health

---

- **Justified = no**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Supports the position that the cleanups are unjustified, an undue burden, and/or a waste of resources

---

- **Justified = yes**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Supports the position that the cleanups are justified and necessary to protect students/public

---

- **Lead arsenate**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Mentions lead arsenate by name or by obvious description, i.e. the spraying of chemicals/lead and arsenic on orchards to battle the codling moth before 1950

- **Medical Effects**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/17/16 by Jessie Martin

Comment:

> Explains potential medical effects of lead and/or arsenic - poisoning, cancer, IQ, developmental issues, birth defects, etc.

- **Orchards/Ag - defensive**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

> Is defensive of the practices and/or history of orchardists/agriculture

---

- **Reporting Error**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/18/16 by Jessie Martin

Comment:

> Cites an error in contamination levels or blood lead levels: these mixed messages could feed the idea that risk is exaggerated.
>
> DoH's blood lead level testing procedures resulted in greater than actual incidence (i.e. double counting)
>
> The paper ran an article that stated lead levels were double the allowable limit at Sunnyslope and then retracted with "LEAD LEVELS NOT EXCESSIVE"

- **Risk = no**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:
> Denies potential for harm

- **Risk = uncertain**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:
> Asserts that risks are unknown: may be some, may be none, etc. (This is often used to say the cleanups are unjustified.)

- **Risk = yes**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:
> Supports the potential for harm

- **School Cleanup**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:
> Mentions the cleanup(s) of a school(s) in the Wenatchee School District, may or may not mention specific school(s)

- **School Contamination**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:
> Mentions the contamination of school soil with lead and arsenic (These are pre-cleanup discussions of the presence of the toxins on school grounds.)

- **Scientifically inaccurate**

Created: 8/17/16 by Jessie Martin, **Modified:** 8/17/16 by Jessie Martin

Comment:

Information that contradicts the most current scientific research - typically takes the form of underestimating or denying risk/hazard of lead and/or arsenic exposure

---

- **Source - orchards/ag**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

Cites orchards/agriculture as source of contamination

- **Source - other**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

Cites some other potential source for elevated blood lead levels in NCW

- **Title of Article**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

Comment:

All article titles are coded with this for use in a co-ocurrence analysis

---

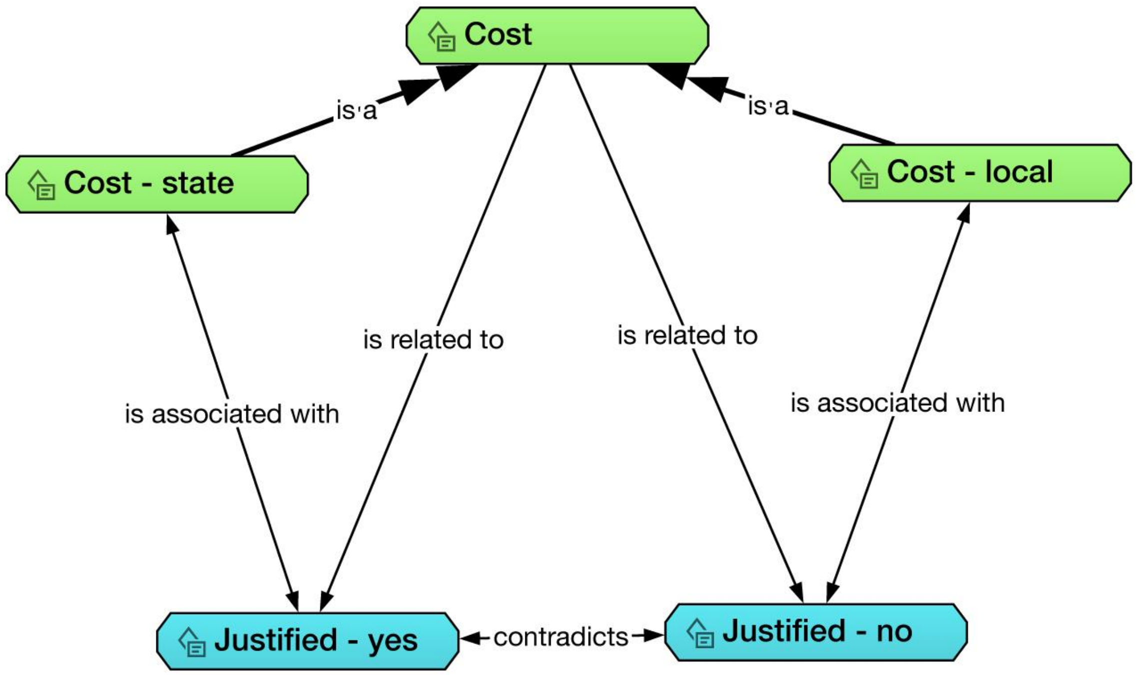
- **Ubiquitous**

Created: 8/10/16 by Jessie Martin, **Modified:** 8/10/16 by Jessie Martin

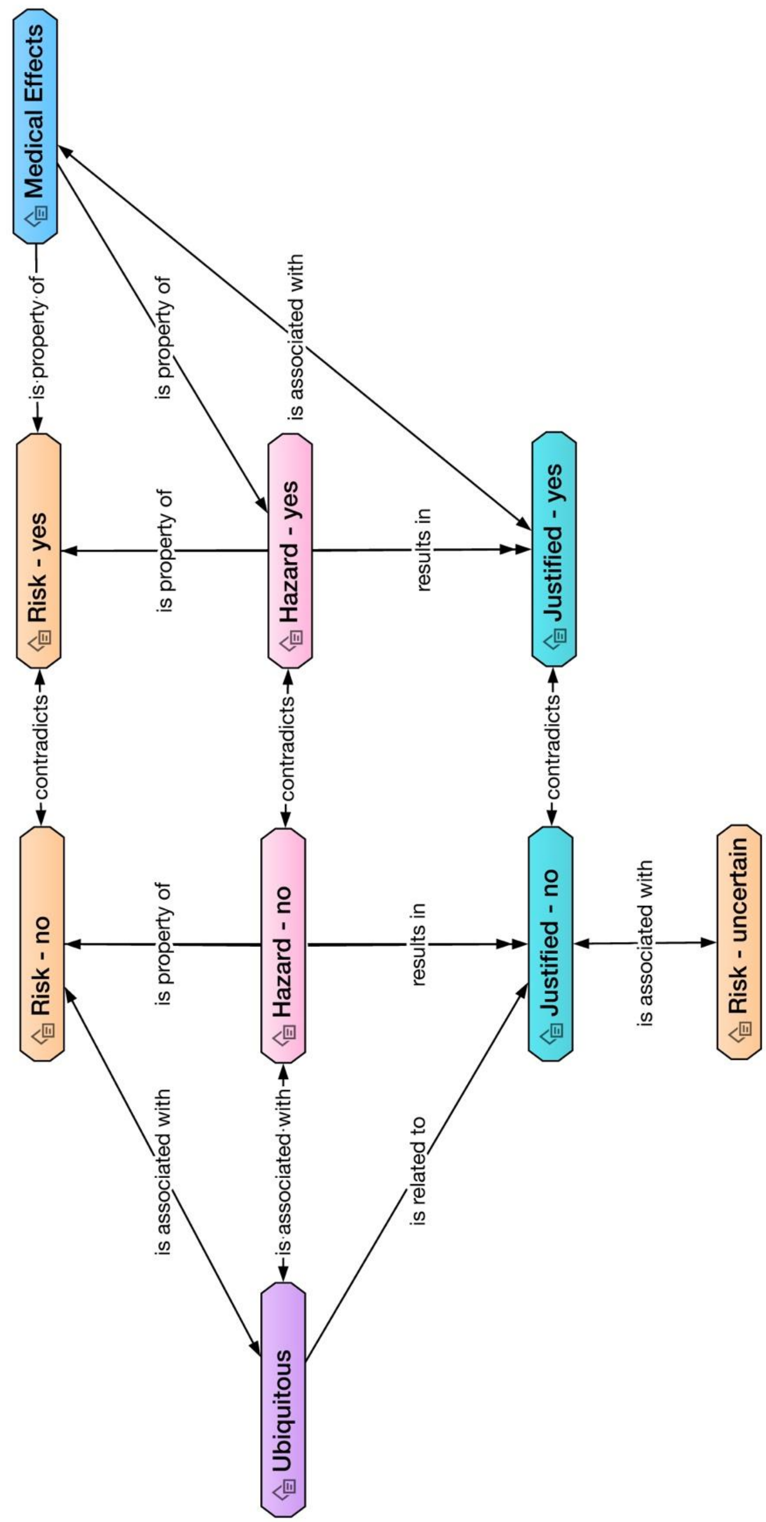
Comment:

A statement that describes lead/lead arsenate/soil contamination/etc. as being pervasive or unavoidable in the region, i.e. a "fact of life" in NCW - often accompanied by some anecdotal observations that it causes no harm

I. Code Networks

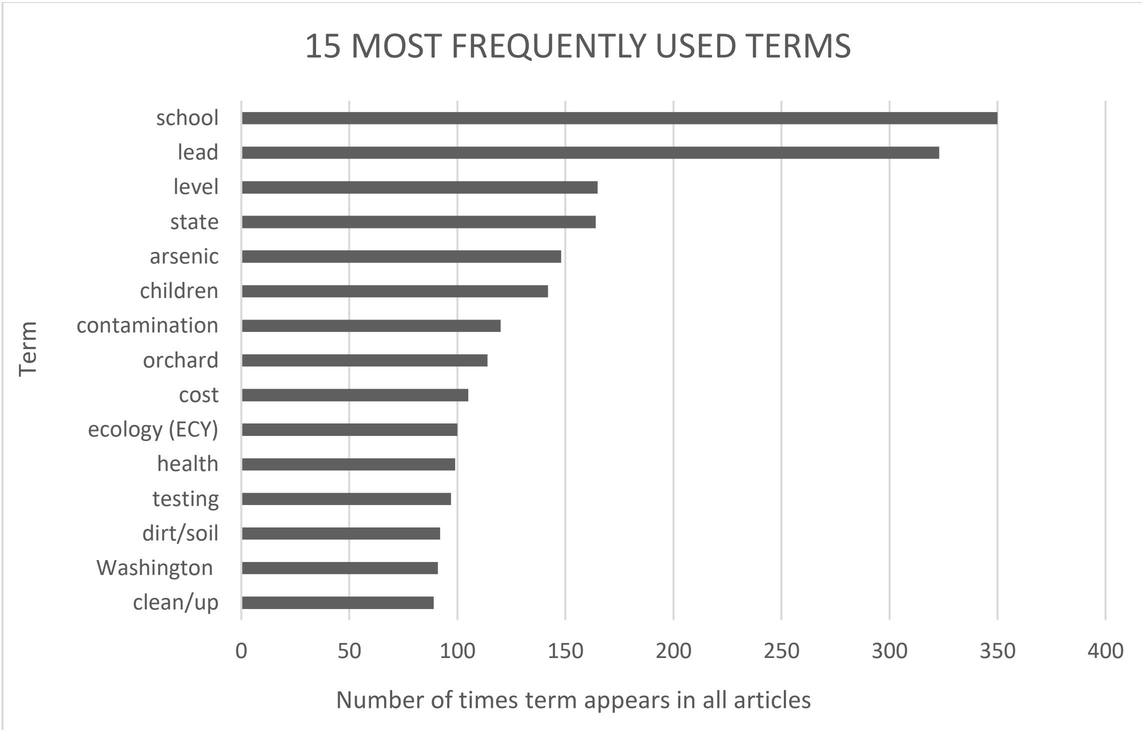


Cost burden as a determinant of cleanup justification



Hazard, risk perception, and cleanup justification

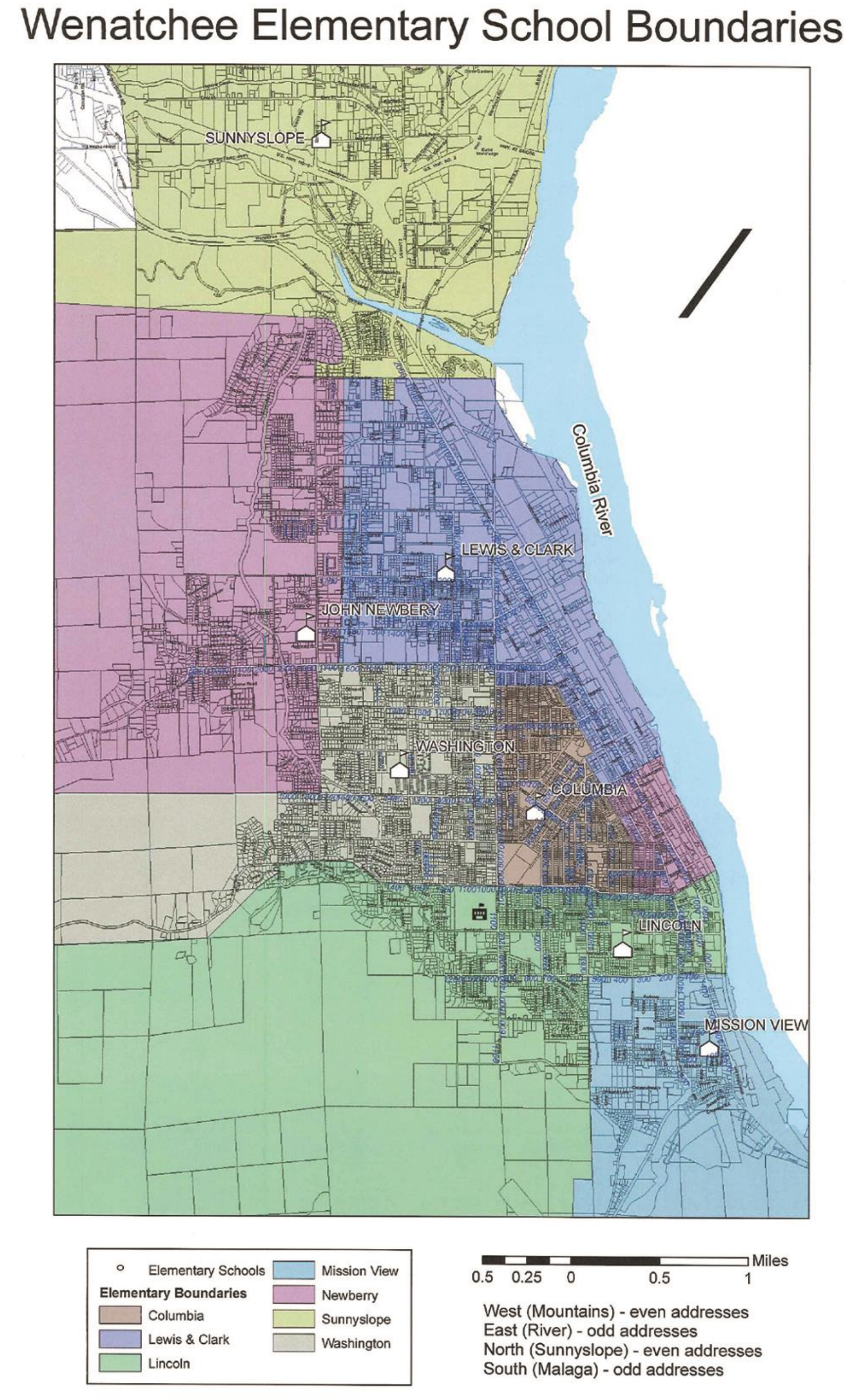
J. Media Analysis - Word Counts



K. Media Analysis - Most Frequent Code Co-occurrences

Co-occuring codes			Frequency of co-occurrence
Cost	+	Cost = Local	29
Expert	+	Risk = Yes	27
Expert	+	Source = Orchards/ag	17
Expert	+	Medical Effects	11
Lead arsenate	+	Source - Orchards/ag	11
Risk – yes	+	Medical Effects	11
Cost - state	+	School Cleanup	10
Cost	+	School Contamination	10
Expert	+	Hazard = Yes	10
Expert	+	Hazard = Yes	10

L. Elementary School Attendance Map



M. Middle School Attendance Map