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The Economic Impacts of Soil Remediation Efforts at Lead Arsenate Contaminated Sites in Yakima County: A Hedonic Approach

Seth Urbanski
urbanskis@cwu.edu

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THE ECONOMIC IMPACTS OF SOIL REMEDIATION EFFORTS
AT LEAD ARSENATE CONTAMINATED SITES
IN YAKIMA COUNTY: A HEDONIC APPROACH

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
Seth James Urbanski
May 2020

CENTRAL WASHINGTON UNIVERSITY

Graduate Studies

We hereby approve the thesis of

Seth James Urbanski

Candidate for the degree of Master of Science

APPROVED FOR THE GRADUATE FACULTY

Dr. Toni Sipic, Committee Co-Chair

Dr. Chad Wassel, Committee Co-Chair

Ms. Jessica Martin

Dr. Kevin Archer, Dean of Graduate Studies

ABSTRACT

THE ECONOMIC IMPACTS OF SOIL REMEDIATION EFFORTS
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Area-wide lead-arsenate contamination stemming from the widespread use of pesticides in the early 1900s poses a serious health risk to the residents of Yakima, Washington. Soil testing for contaminants resulted in the Department of Ecology funding the remediation of 6 elementary schools in Yakima, Washington where unsafe levels of lead and arsenic were found in the topsoil. This study will evaluate the impact that these remediation projects have had on nearby real estate values through the use of GIS analysis and multivariate hedonic pricing models. We expect to find a negative price effect on real estate values following the announcement of remediation efforts and a more significant positive price effect following the completion of the remediation. These price effects will be used in conducting a cost-benefit analysis. These findings can be used by policymakers to inform decisions regarding funding for future remediation efforts

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TABLE OF CONTENTS

Chapter		Page
I	INTRODUCTION.....	1
	Research Overview.....	1
	Defining Area-wide Soil Contamination.....	4
	Washington State’s Area-Wide Soil Contamination Task Force	6
II	LITERATURE REVIEW	11
	Literature Overview	11
	Lead-Arsenate: Historical Uses and Health Risks	11
	Lead-Arsenate: Remediation Efforts and the Public Response	14
	Lead-Arsenate: Economic Impacts and Evaluation Methods	17
III	STUDY AREA	21
	Area Overview.....	21
	Regional Economics.....	21
	Yakima School District.....	26
	Lead-Arsenate Cleanup Sites.....	27
	Yakima County Soils.....	29
IV	DATA COLLECTION AND VARIABLE CREATION	30
	Housing Data.....	30
	School Cleanup Data	34
	Treatment Group Variable Creation	38
V	METHODS.....	41
	Hedonic Regression Modelling.....	41
	Cost-benefit Analysis.....	48
VI	RESULTS	53
	Hedonic Analysis Results.....	53
	Cost-Benefit Analysis Results	65
VII	DISCUSSION.....	67
	Discussion of Findings	67

TABLE OF CONTENTS (CONTINUED)

Chapter	Page
Discussion of Policy Recommendations.....	69
Discussion of Future Research	73
REFERENCES.....	75
APPENDICES	82
Appendix A—Variable Definitions.....	82
Appendix B—Stata Code	84

LIST OF TABLES

Table	Page
1	Key 2016 Performance Indicators for YSD Compared to WA State 26
2	Lead-Arsenate Testing Results at Yakima School Sites..... 27
3	Summary Statistics for Yakima Home Sales Dataset (n=18757)..... 33
4	Summary Statistics for Subset of Home Sales (2003-2018) Occurring Within 1927 Airphoto Extent (n=11422)34
5	School Site Cleanup Timelines 34
6	Remediation Costs for Yakima Elementary School Cleanups..... 35
7	Treated (Concentric) Residential Home Sale Counts for Remediated Yakima Elementary School Boundary Areas (n=18757) 39
8	Treated (Non-Concentric) Residential Home Sale Counts for Remediated Yakima Elementary School Boundary Areas (n=18757) 40
9	Yakima Elementary School Remediation Cost Figures and Cost Estimate for Gilbert Elementary 49
10	Tax Benefit Calculations for Cost-Benefit Analysis..... 51
11	Health Benefits for Cost-Benefit Analysis..... 52
12	Results for Preliminary Regression Model (Impact of a home being built on former orchardlands).....53
13	Results for Start Treatment Only Regression Model (Form A)..... 55
14	Results for Listing Treatment Only Regression Model (Form B) 57
15	Results for Cleanup End Treatment Only Regression Model (Form C)..... 59
16	Results for Delisting Treatment Only Regression Model (Form D) 61
17	Results for All Treatments Included Regression Model (Form E)..... 63
18	Cost Benefit Analysis Calculation and Net Benefit 65

LIST OF TABLES (CONTINUED)

Table		Page
19	Hypothetical Tax and Home Seller Benefits (Assuming all schools de-listed and consistent 10.4% price increase for de-listing).....	70

LIST OF FIGURES

Figure		Page
1.1	Georeferenced 1927 Aerial Photography Flown Over Yakima.....	24
1.2	Extent of Former Orchardlands in Yakima Washington (1927).....	25
2	Lead-Arsenate Cleanup Sites in Yakima, Washington	28
3	Yakima School District Boundaries and Home Sale Records	37
4	Time-series Graph of “Start” Treatment Price Impacts.....	56
5	Time-series Graph of “Listing” Treatment Price Impacts	58
6	Time-series Graph of “Ending” Treatment Price Impacts	60
7	Time-series Graph of “Delisting” Treatment Price Impacts	62

CHAPTER I

INTRODUCTION

1.1 Research Overview

In the early 1900s, Washington State's burgeoning apple industry was facing a crisis. This crisis centered around the introduction of the codling moth; an invasive species of moth which lays its eggs primarily in apples, pears, and other pome fruits. The codling moth larvae eat the host fruit after hatching, rendering the fruit rotten, inedible, and useless to Washington's orchard owners. In response to the mounting crisis, farmers began spraying their orchards heavily with pesticides. The standard chemical for pest control at the time was lead arsenate (PbHAsO_4), which was initially very effective in controlling the codling moth population. By the 1930s, however, the moths had grown resistant to lead arsenate. This prompted orchard owners to begin spraying the pesticide in heavier doses and with greater frequency (Schick and Flatt 2015). Heavy spraying of lead arsenate pesticides continued in Eastern Washington's orchards from the 1930s until the late 1940s when they were banned and replaced with a new pesticide: DDT. Though they have long since stopped using lead arsenate pesticides in Eastern Washington, the legacy contamination still persists in the topsoil of former orchard lands. It is estimated that as many as 200,000 acres of former orchard lands within Washington State are affected by lead-arsenate contamination, with as many as 60,000 acres of contaminated soil in Yakima County alone. (ECY 2003). The lingering effects of this widespread contamination are being felt more acutely today than ever before as cities and neighborhoods continue to expand outward into contaminated former orchard lands.

Lead-arsenate contaminated soil poses significant health risks to those exposed even at relatively low concentrations (Tolins et al. 2014). Soil testing in Eastern Washington conducted

by the Department of Ecology has identified area-wide lead concentrations averaging around 700ppm (parts per million) in residential soil and up to 4,000ppm on orchard lands. These findings are well in excess of the Model Toxics Control Act's (MTCA) safe threshold of 250ppm for lead (ECY 2003). In 2002, the Area-Wide Soil Contamination Task Force (Task Force) was commissioned to study the extent of former orchard lands contamination in Eastern Washington and to identify strategies for cleanup and remediation. The Task Force's findings resulted in the Department of Ecology funding the remediation of 26 schools and 2 parks in Eastern Washington, including 8 schools and 2 parks in Yakima County (ECY 2016). Despite the ongoing need for remediation projects, little has been done to address the issue following the initial wave of cleanups, mainly due to concerns over the high cost of remediation. Ecology Central Washington Director Valerie Bound was quoted in the work of Schick and Flatt (2015), saying that "the fund for lead-arsenate remediation at school sites ran dry even before two of the contaminated schools slated for cleanup within Yakima County could be finished." In the same interview, Bound went on to say that she hasn't asked for more money for the lead-arsenate remediation and has no plans to request additional funding since the public has not pushed for more action.

The purpose of this study is to identify whether or not the remediation of lead arsenate pesticides from six schools in the city of Yakima, Washington has had any impact on nearby residential property values using hedonic modelling. These mathematical models can be used to examine large data sets and identify how given factors and characteristics tend to impact a good or a product's selling price. One such model is employed in this study to determine how a house's proximity to lead-arsenate remediation sites affects its selling price in conjunction with other factors including the media coverage of the remediation process, house square footage, age,

and sale date. To accomplish this, we have 1) determined which property characteristics (building age, square footage, number of bathrooms, acreage, etc.) have the greatest effects on residential property values, and determined the magnitude of these effects using a hedonic pricing model, 2) identified what impact lead-arsenic pesticide cleanup operations have had on Yakima County's residential property values by incorporating variables into the hedonic model for distance to a cleanup site as well as time elapsed between the project's conclusion and the home's sale date, 3) determined to what extent the economic impact from remediation has been affected by public perception and media coverage of the health risks posed by lead-arsenate, 4) determined whether the current Task Force and MTCA practices and guidelines for soil remediation could be improved or made more efficient using cost-benefit analysis, 5) provided a reference for policymakers to use in determining the total economic costs and benefits of soil cleanup and remediation projects.

Despite the continued need for soil remediation projects in Yakima County, a significant research gap exists in Yakima County with regards to the economic impacts of such projects. This inquiry helps to address this research gap and provide policy makers with more information regarding the economic costs and benefits of lead-arsenic soil remediation so that they will be better equipped to make well informed decisions on future remediation projects. It is important for policy makers to consider the economic impacts of soil remediation in addition to the clear social and health benefits associated with cleaning lead arsenic residue from parks and schools in order to conduct accurate cost-benefit analyses on remediation projects. This study continues to build upon a growing body of research detailing the economic impacts of lead-arsenic soil remediation in some of Eastern Washington's other counties. This research additionally benefits local communities by highlighting the need for ongoing cleanup and remediation actions across

the state which protect public health and build community wealth through increased real estate asset values.

It is also worth noting that the data and analysis put forth by this research has far-reaching applications beyond just the state of Washington. According to the National Resources Conservation Service (NRCS) working in conjunction with the United States Department of Agriculture (USDA), 11.1 million acres of cropland have been converted to developed land from 1982 to 2007 (NRCS 2007). As more and more former croplands and orchardlands are developed across the United States, it becomes increasingly important that policymakers and agency planners are able to understand and consider private preferences related to the health risks posed by potential area-wide soil contamination when planning for development, remediation, and abatement projects at these legacy agricultural sites.

1.2 Defining Area-wide Soil Contamination

In a 2003 publication addressing area-wide lead and arsenic contamination response strategies, the Washington State Department of Ecology (DOE) defined area-wide soil contamination as low-to-moderate level contamination which has been dispersed over large geographic areas (ECY 2003). The “low-to-moderate” designation is defined differently for both lead and arsenic, as arsenic levels up to 100ppm and lead levels up to 700ppm qualify as area-wide contamination. According to the DOE, up to 677,000 acres of land within Washington State have been designated as affected by area-wide lead and arsenic soil contamination. This land can be split into two broad categories: land affected by pollution from historic smelters (approximately 489,000 acres) and land affected by legacy lead-arsenate pesticide use (approximately 188,000 acres) (ECY 2003).

The land affected by historic smelters lies to the west of Washington's Cascade Mountains in cities such as Tacoma, Everett, and Harbor Island where ore and metal smelters were operated during the early 20th century. These smelters emitted toxic and highly concentrated plumes of airborne lead and arsenic particulate matter into their surrounding areas.

Land impacted by legacy agricultural pesticides can be found primarily in counties east of the Cascades in Washington State where a majority of the state's orchards and large-scale agriculture can be found. Significant amounts of area-wide soil contamination from legacy orchard operations can be found in Spokane, Chelan, Yakima, and Okanogan counties. Among these counties, Yakima is estimated to contain the most contaminated land with approximately 60,000 acres of polluted soil (ECY 2012). It is worth noting that any land meeting the threshold for area-wide lead contamination (approximately 700ppm) will be well in excess of the MTCA's minimum safe threshold for human lead exposure, set at 250ppm (ECY 2003).

When it comes to addressing and remediating area-wide soil contamination, there are some unique issues and challenges which require consideration. One such issue is the vast geographic scale at which this contamination occurs. Given that many tens of thousands of acres may be polluted in Yakima County alone, the scale of the cleanup is significantly greater than that addressed by the typical state or federal cleanup program (ECY 2003). Another major challenge is posed by varying degrees of public awareness and risk perception relative to the health hazard that area-wide lead-arsenate contamination presents. Soil contamination is often very difficult to identify without scientific testing, so people are often unaware that their homes, schools, or parks may be contaminated with lead-arsenate. Without this awareness, they are unable to make informed decisions to reduce health or financial impacts (ECY 2003). Even given perfect information regarding the risks posed by the presence of lead-arsenate

contamination, there will be wide variations in how individuals perceive that risk and act accordingly. Factors such as familiarity with the risk, the degree to which they control their exposure to the risk, and whether children are exposed to the risk can all influence an individual's risk perception and avoidance behaviors (ECY 2003).

1.3 Washington State's Area-Wide Soil Contamination Task Force

Considering the aforementioned unique challenges posed by area-wide soil contamination in Washington State, it became apparent to the Departments of Agriculture, Ecology, Health, and Community Trade and Economic Development that a collaborative effort would be necessary to address this contamination. To this end, the Area-wide Soil Contamination Task Force (Task Force) was commissioned by these four agencies in January 2002 in order to "provide recommendations on how the agencies might improve the ways [they] respond to elevated levels of arsenic and lead in soils in Washington State" (ECY 2003). The Task Force consisted of seventeen individuals with varying backgrounds and areas of expertise who represented potentially affected stakeholder groups. The Task Force members represented diverse interests including business, agriculture, environment, local government and schools (ECY 2003).

The Task Force's primary goal was to come up with recommendations and implementation strategies for five key soil-contamination related objectives. These objectives are as follows; 1) "improve public awareness and understanding of area-wide soil contamination concerns and solutions," 2) "collect and evaluate information to support decisions on measures for reducing the potential exposure to arsenic and lead in soils," 3) "reduce the potential for exposure to arsenic and lead in soils at developed properties," 4) "reduce the potential for exposure to arsenic and lead in soils at properties under development," 5) "improve institutional

capabilities for responding to area-wide soil contamination” (ECY 2003). When it came time for the Task Force to begin working towards these goals, they faced a number of challenges and difficulties.

One significant challenge faced by the Task Force was posed by Washington State’s legal code and laws for information disclosure in real estate transactions. Washington State law requires that real estate sellers disclose the presence of soil contamination on the property for sale only if the presence of said contamination has been explicitly tested for and confirmed (RCW 64.06.020). Testing is in no way required by law, so sellers may often elect to forgo testing for fear of discovering contamination which may lower their property’s value. Segerson (1997) writes that such informational asymmetry can lead to market inefficiencies and an inequitable transfer of liability from the seller to the buyer. This issue of informational asymmetry can be especially prevalent in places like Yakima where sellers may have a general idea regarding the presence of local area-wide soil contamination despite never explicitly testing for it on their property. In this case, the sellers have no legal requirement to disclose the possible presence of soil contamination and are in fact incentivized to avoid testing for fear of finding something which would require disclosure and thus decrease their property’s value (Schick and Flatt 2015; Segerson 1997). Segerson (1994) does suggest that given the correct market conditions there could be an incentive for home sellers to test for contaminants, remediate the property, and then sell at a higher price point thus recouping the cost of abatement. This was a major point of contention for the Task Force members, as there was significant disagreement over whether more mandatory soil testing would benefit or harm the real estate industry overall.

In the Task Force’s final recommendations, it was suggested that the Task Force’s Charting Agencies “work with and through the Washington Association of Realtors (WAR) to

strongly encourage real estate agents to use the lead-based paint disclosure form and Environmental Protection Agency (EPA) pamphlet for all transactions or use similar disclosure documentation where area-wide soil contamination is likely” (ECY 2003). According to Schick and Flatt (2015), implementation and adoption of this recommendation has been woefully inadequate given that Task Force real estate industry representative Steven Kelley was never given the opportunity to present the Task Force’s recommendations to the WAR.

Among the greatest challenges faced by the Task Force revolved around securing funding for soil testing and remediation statewide. The bulk of this money was secured from the MCTA (Washington State’s environmental cleanup law), which has set aside a fund to provide for the maintenance Washington State’s environmental health while addressing toxic substance contamination (ECY 2003). The MCTA fund’s coffers are replenished both by Washington State’s Hazardous Substance Tax along with penalties and cleanup costs recovered from polluters (RCW 70.105D.190). This means that MTCA funding relies primarily on Hazardous Substance Tax revenues from the sale of petroleum products and pesticides in the state (RCW 82.21.030). Given that petroleum markets are prone to severe fluctuations and price volatility, the flow of funds for soil testing and remediation secured from the MTCA has been both unreliable in its timing and overall wholly insufficient to address area-wide contamination across the entire state (Schick and Flatt 2015).

These issues of insufficient funding for remediation have been further exacerbated for the former orchardlands of eastern Washington by the state’s legal code governing standards of liability and settlements for hazardous substance release. Under RCW 70.105D.040, owners and operators of facilities releasing hazardous substances may be held liable for remediation costs. Due to this regulation, lead-arsenate remediation efforts in Western Washington have been able

to supplement their funding through legal settlements with the corporations which operated the polluting smelters. For example, in 2009, a sum of \$95 million dollars was procured in a settlement with the American Smelting and Refining Company LLC for use in remediating the Tacoma, Washington smelter site (ECY n.d.).

For the former orchardlands of eastern Washington, however, there is no such additional settlement funding to aid remediation efforts. This is because Washington State law explicitly protects from liability “any person who, for the purpose of growing food crops, applies pesticides or fertilizers without negligence and in accordance with all applicable laws and regulations” (RCW 70.105D.040). For Washington State’s orchard owners in the early 1900s, the widespread use of lead-arsenate based pesticide was sanctioned and even encouraged by government agencies as a response measure to control the codling moth invasion which may have otherwise decimated the United States’ tree fruit industry (Schick and Flatt 2015; Hood 2006). In the present day, this means that no current or former orchard owners may be held liable for the historical application of legacy pesticides like lead-arsenate which, at the time, had been approved for use by the United States Department of Agriculture. Without any legal settlement money to supplement the often inadequate MTCA funding, remediation efforts in eastern Washington have been especially prone to funding shortages (Schick and Flatt 2015).

Despite these hurdles and more, the Task Force eventually delivered their recommendations to the four Chartering Agencies after eighteen months of deliberation. These recommendations included general suggestions for improving public health and general awareness of the potential area-wide contamination along with recommendations for addressing specific land-use scenarios in potentially contaminated zones such as child use areas and plots used for cultivating root vegetables (ECY 2003). It is this set of recommendations which resulted

in the Washington State Department of Ecology funding soil remediation projects at 26 schools and 2 parks in central and eastern Washington (ECY 2016). Included among these 26 schools were 6 elementary schools within the city of Yakima, Washington which serve as the focal point of this study's analysis.

CHAPTER II

LITERATURE REVIEW

2.1 Literature Overview

The literature relevant to my study can be divided up into three broad categories. These categories include the historical uses and health risks associated with lead-arsenate pesticides, the public's response to these risks and to past cleanup operations, and the methods to be employed in evaluating the economic impact of lead-arsenate contamination and remediation.

2.2 Lead-Arsenate: Historical Uses and Health Risks

The first objective within this section is to explain the history of lead-arsenate pesticides and their uses in Washington State. The works of Peryea (1998), Hood (2006), and Schick and Flatt (2015) are critical for establishing a historical context for the lead-arsenate pollution now found in Eastern Washington. These articles explain how and why lead-arsenate was used so heavily for pest control in Washington State's orchards during the early 1900s. The work of Peryea (1998) is particularly useful in establishing a context for the widespread use of lead-arsenate as a pesticide during the early 20th century. In this work, Peryea notes that the pesticide was applied as a liquid slurry first via handgun sprayers and later tractor-mounted sprayers. Lead-arsenate was used as a pesticide in part for its extreme toxicity to the invasive codling moths and also because the lead-arsenate slurry adhered well to the surfaces of plants, allowing for longer lasting pesticidal effects (Peryea 1998). The spraying of lead-arsenate pesticides in Washington State began in the early 1900s and was largely phased out by 1948 when the new pesticide DDT became available.

The repeated application of this pesticide eventually caused lead and arsenic to accumulate in the topsoil, where it typically remained static in the uppermost layers of topsoil

(Veneman et al. 1983). In Chaney and Ryan (1994), it is noted that very little lead and arsenic contamination is found in the orchard trees themselves despite heavy pesticide application (a phenomenon known as the “soil-plant barrier”). Other crops, including tuberous and leafy vegetables like carrots or lettuce, have been found to contain harmful levels of lead when grown in soil contaminated by legacy lead-arsenate pesticides (Chaney and Ryan 1994). It is noted that the primary pathways for human exposure to lead-arsenate pesticide residue are direct ingestion of contaminated soil, ingestion of leafy or root vegetables grown on contaminated soil, and ingestion of livestock which consumed forages grown on contaminated soils (Chaney and Ryan 1994). For the purpose of our study, direct ingestion of contaminated soil will be the primary exposure pathway of note given that the contaminated sites in question are now operating as schools rather than farmlands.

Hood (2006) and Schick and Flatt (2015) then build upon this work by outlining the ways in which lead-arsenate was used specifically in Eastern Washington. According to Schick and Flatt (2015), hotspots for legacy lead-arsenate pesticide application in Washington State include Chelan, Yakima, and Spokane counties. Within Yakima and Chelan counties, the two largest cities with significant amounts of lead-arsenate contamination are Yakima and Wenatchee, respectively. These articles also introduce some of the growing health concerns stemming from increased residential development into contaminated former orchard lands. Schick and Flatt (2015) in particular mentions that in addition to the schools, parks, and residential neighborhoods which may have been built on contaminated soil, the cities of Yakima and Wenatchee have a combined 340 childcare centers which are not required by law to test for the possible presence of lead-arsenate residue in their soils. With so many people and children in particular living in areas where they may frequently come into contact with lead-arsenate residue, it is crucial to

understand the health risks associated with lead and arsenic exposure in order to grasp the severity and magnitude of the issue.

The second objective within this section is to outline some of the health risks related to lead and arsenic exposure. Integral to the understanding of these risks is the work of Mielke and Reagan (1998). Their article, which is later expanded upon by Wolz et al. (2003), identifies soil as a critical pathway of human lead exposure. This is due to the fact that lead particles bonded with soil are very easily inhaled or ingested with airborne dust. Lead-contaminated dust is also easily carried into homes on the residents' shoes and clothing where it may then be ingested or inhaled by others who may not otherwise have had first-hand exposure to the contaminated soil (Wolz et al. 2003; Mielke and Reagan 1998). These articles highlight the dangers stemming from this type of area-wide soil contamination with regards to human exposure.

Equally important to understanding the health dangers posed by lead-arsenate contamination are the works of Millichap (1987), Rutter et al. (1983), Ruby et al. (1999), Taylor et al. (2013), and EPA (2003). Given that the cleanup sites in my study area are all elementary schools, Taylor et al. (2013), Ruby et al. (1999), and Millichap (1987) are particularly useful pieces of literature as they primarily discuss the impacts that lead exposure has on the health and development of children. The severity of the risk posed to children by lead-arsenate contamination is highlighted in Ruby et al. (1999), which found that lead absorption rates in children are between 3.5 and 5.7 times higher than among adults. The work published by the EPA (2003) is also particularly useful for this study as it contains estimates of how much lead could be ingested over given time periods due to contaminated soil exposure. This study estimated that mean bloodstream lead levels of up to 15 µg/dL (micrograms per deciliter) could be observed in young children and toddlers who visited lead-contaminated soil sites 4 times per

week over the course of a year (EPA 2003). A study published by the Center for Disease Control (2007) found that lead concentrations greater than 10 µg/dL in the bloodstreams of developing children are tied to greatly increased risks of developing severe neurological or behavioral disorders.

There are serious health risks associated with arsenic exposure as well, especially when said exposure occurs at a young age. The World Health Organization has noted that long-term effects of arsenic ingestion include greatly increased risk of various cancers, diabetes, pulmonary disease, and cardiovascular disease (WHO n.d.). Exposure to arsenic at a young age has also been associated with deficits in memory and intelligence, with some neurocognitive consequences only manifesting later in life (Tolins et al. 2014). Significant health risks are posed by lead-arsenate pollution and thus, heavy social costs are incurred through exposure such as diminished IQ in children and more frequent hospital visits or health complications for adults (Ruby et al. 1999, CDC 2007; Taylor et al. 2013).

2.3 Lead-Arsenate: Remediation Efforts and the Public Response

One of the purposes that this study aims to fulfill is to determine whether the current Task Force and MTCA practices and guidelines for soil remediation have been a cost-efficient solution to the problem using cost-benefit analysis. The works of Peryea (1998), Hood (2006), and ECY (2003) describe some of the most common methods for soil remediation such as contaminated soil sequestration or soil excavation. Peryea (1998) notes that removal of the lead and arsenic is typically the preferred solution, though complete removal may be cost prohibitive depending on the depth of the contaminated soil. Encapsulation of the contaminated soils with fine mesh cloth and uncontaminated topsoil is also considered an acceptable practice for remediation. Encapsulation (or capping) is, however, subject to “physical disturbance by

humans, burrowing animals, and solifluction which can re-expose the contaminated subsoil” (Peryea 1998). In cases where capping is employed as a remediation strategy, periodic testing is often required to ensure that contaminated subsoil has not been re-exposed. Dilution of the contamination through the mixing of uncontaminated soils is not considered an acceptable cleanup measure (Peryea 1998).

ECY (2003) and Peryea (1998) also contain cost estimates pertaining to the different remediation methods, which will be crucial to include for any cost-benefit analysis. Peryea (1998) notes that cost estimates for the removal of contaminated soil can range from \$25,000 to \$1 million per acre depending on the depth of contamination. The site action reports published in ECY (2003) additionally detail the exact costs of remediation at each of the six elementary schools in Yakima, Washington which received cleanups. These costs ranged from approximately \$150,000 to \$250,000 per school site (ECY 2003).

Equally important for the cost-benefit analysis will be a breakdown of the benefits gained from remediation, which in this case could also be described as the costs incurred due to a lack of remediation. These costs (or unrealized benefits) are well detailed in a study conducted by Muennig (2009) which modelled the total social cost of childhood lead exposure. This model accounts for factors such as total lifetime earnings, improvements in health, and reduced crime costs to estimate the annual savings to society from reducing a child’s lead exposure by a certain amount. This work was expanded upon by Gould (2009), who calculated an average return on investment of between \$17 and \$221 in net benefits and savings to society for every dollar spent preventing lead exposure. A study conducted by Pichery et al. (2011) in France found that children with bloodstream lead concentrations of at least 15 µg/dL (well within the expected bloodstream absorption range for children visiting lead-arsenate contaminated sites in Yakima)

would have increased healthcare costs of approximately €2,931.64 (\$3,304.79) over their lifetimes. The estimates found by these studies will be applied to our study area of Yakima, Washington using benefit transfer.

Another key objective for our study is determining to what extent the economic impact from remediation has been affected by public perception and media coverage of the health risks posed by lead-arsenate. As such, reviewing information regarding the public response to remediation efforts will be crucial to this study and to gaining a complete understanding of the issue at hand. The works of Slovic (2000), McCluskey and Rausser (2003), and Martin (2017) will provide a framework for determining how public perception of lead-arsenate pollution and remediation has factored into the economic impacts of contamination and cleanup. The articles written by McCluskey and Rausser (2003) and later Martin (2017) are crucial to this research, as both note that the media plays an integral role in determining how the public perceives any environmental risk. Martin (2017) in particular found that the release of news media articles mentioning the presence of lead-arsenate contamination at school sites in Wentachee, Washington decreased the selling price of homes sold within 31-60 days of an article's publication by 9.33% on average.

The work of Slovic (2000) specifically covers historical public responses to lead contamination when compared with other known toxins or pollutants. Slovic (2000) found that most people become aware of environmental dangers through media coverage. This means that the degree of media coverage plays a major role in how individuals assess the risks associated with environmental hazards like area-wide lead-arsenate contamination. The findings of McCluskey et al. (2001) suggest that for individuals making pricing decisions regarding environmental hazards, perceived risks have a greater impact on prices than the actual risks.

They concluded that perceived risks have a significant impact on home values, and that these risk perceptions can be influenced by the media (McCluskey et al. 2001). These authors detail how media coverage, community awareness, and risk perception strongly affect and modify the overall economic impacts of lead-arsenate soil contamination.

2.4 Lead-Arsenate: Economic Impacts and Evaluation Methods

Rosen (1974) was the first to apply a hedonic pricing model to real estate values, thus demonstrating that housing prices can be affected by a variety of attributes and characteristics of the property. The hedonic models employed by Rosen (1974) are capable of estimating the impact that each home characteristic (for example, square footage, acreage, number of bedrooms, etc.) has on the sale price of a typical home based on a dataset detailing home sale prices and property attributes. Among those characteristics affecting home values are factors relevant to this study such as environmental health and the presence of harmful pollutants or contamination. Building on the previous work of Rosen (1974); Palmquist (1988) applied the concept of hedonic modelling directly to measuring the relationship between environmental quality and property values. The hedonic models created by Palmquist (1988) demonstrate that environmental quality is a measurable characteristic of a property which gets implicitly factored into that property's value. As such, hedonic models containing proxy variables for local environmental quality are able to extract the impact that local contamination or pollution tends to have on home sale prices in a given area. For this reason, hedonic housing price experiments are considered the 'gold standard' approach in the field of environmental economics when it comes to placing a value on environmental quality (Martin 2017).

More recent studies have applied this hedonic approach to evaluating the economic impact of various types of pollution including air, water, and soil contamination. Among these

studies are the works of Mihaescu (2010), Schwarz et al. (2017), and Martin (2017) which evaluate the impact of brownfield (contaminated soil) sites on residential property values. The Mihaescu (2010) study also includes estimates for the total amount of tax revenue lost due to property values being diminished by nearby contamination. It was estimated that depressed property values due to nearby contaminated sites were costing the City of Cincinnati, Ohio approximately \$332,585 in annual property tax revenues (Mihaescu 2010). In the work of Schwarz et al. (2017), a hedonic housing price model is employed to determine the impact of brownfield remediation projects on nearby housing prices in Charlotte, North Carolina. The environmental quality proxy variables employed in this study's hedonic models were intended to capture the impacts of both the announcement and completion of remediation efforts on nearby home sale prices. The authors' models estimated that houses selling after the announcement of planned remediation efforts (at brownfields within 0.5 miles) saw an average price increase of 30%, while houses selling after the completion of remediation efforts (within 0.5 miles) saw an additional 12% increase in sales prices (Schwarz et al. 2017). These price increases led to a total estimated economic benefit from remediation of approximately \$4 million. The greater magnitude of price impacts observed following the announcement of cleanups as opposed to the actual completion of cleanups in this study serves to underscore the importance of community awareness and risk perceptions as factors which affect how home sale prices respond to nearby contaminated site remediations (Schwarz et al. 2017).

Martin (2017) is an especially valuable study to consider, as this research estimated the impact of school site remediations on residential property values in Wenatchee, Washington using hedonic pricing models. It was determined that the announcement of elementary school cleanups decreased nearby home sale values by approximately 4.5% six months following the

announcement and by as much as 13.5% in the time period 1-1.5 years following the announcement of cleanups. A significant positive price rebound of 5% was observed following cleanups and the delisting of remediated sites (Martin 2017).

A hedonic study conducted by Boyle et al. (2010) explores the particularly strong correlation between contaminated school sites and decreased nearby property values. Given that all 6 remediation sites examined in our study are schools; the work of Boyle et al. (2010) is very instructive as it identifies some of the ways in which school site contamination has impacted property values elsewhere in the world. In this study, it was determined that the primary driver of negative housing price impacts following school site remediation was the announcement of the contamination's discovery and ensuing remediation. Boyle et al. (2010) mentions that while private property owners may have been incentivized to stay quiet about possible soil contamination (to avoid decreasing their own property values), the schools were required to publicize the presence of contamination found on their grounds. This, in turn, led to increased local awareness of the hazard and strong negative price effects in affected areas.

It has repeatedly been demonstrated that following the remediation of a contaminated site, nearby home values tend to rebound. This rebound effect is specifically addressed in the aforementioned research of Martin (2017) as well as in the hedonic housing price research of Gamper-Rambindran and Timmins (2013). This 2013 study found that remediation tended to lead to a 14.7% appreciation in median block-level housing values nearby. These studies detailing price rebound effects from remediation are particularly useful for providing actionable data for policymakers to use when considering new remediation projects, as the magnitude of rebound effects can help inform whether the project is economically efficient (Bryson 2012; Martin 2017).

It is crucial to our study that potential pitfalls and shortcomings associated with hedonic modelling are addressed, and such pitfalls are avoided. Guignet (2013) notes that if hidden characteristics (unaccounted for in the model) are impacting home prices, or if the hedonic model's variables intended to represent environmental quality are not representative of the average homebuyer's knowledge of the issue, then the study's results may be invalid. This represents an example of what is known in hedonic modelling as omitted variable bias. This bias has been addressed and overcome in the hedonic models of Guignet (2013), Kim et al. (2016), and Schwarz et al. (2017) through the inclusion of census block group fixed effects as modelled proxy variables. These census block group fixed effect variables serve as a proxy for factors like the general quality and spatial location of a neighborhood which may be impacting home sale prices in said neighborhood. The inclusion of census block group variables allows for the aforementioned factors to be controlled for in the models so that they do not introduce omitted variable bias into the results.

The work of Brasington and Hite (2005) details another potential bias which may arise from individuals' varying degrees of risk awareness and perception. Their 2005 study measured the degree to which demand for environmental quality varies depending on household demographics such as education levels and number of children. It was determined that individuals with higher levels of educational attainment and households with children have a higher demand and higher willingness to pay for environmental quality (Brasington and Hite 2005). These findings give context to the ways in which the individual homebuyer's knowledge or preferences may influence the value they place on environmental quality (and therefore impact their willingness to pay for property near contaminated sites).

CHAPTER III

STUDY AREA

3.1 Area Overview

This study is focused around determining the impact that lead-arsenate contaminated soil site remediations have had on nearby property values in the city of Yakima, Washington.

Located in south-central Washington's Yakima County, the city of Yakima lies approximately 140 miles east of Seattle and 160 miles west of Spokane. Founded in 1865, Yakima is now both the county seat and largest city in Yakima County, boasting a population of 93,669. The city itself covers an area of 27.8 square miles with a population density of approximately 3,374.3 people per square mile. Of Yakima's 93,669 residents; 47% identify as Hispanic or Latino, which is more than 3 times the statewide average of 13%. The median age in the city is 32.5. Approximately 78.1% of Yakima residents have obtained a high school diploma, which is a much lower figure than the statewide average of 91.3% (U.S. Census 2017). This study will be focused on 6 elementary schools within the Yakima school district which have all been found to have soil lead-arsenate levels sufficient to warrant remediation according to the Washington State Department of Ecology's health and safety standards. These sites were all given a hazardous site ranking of 3 by the Task Force in 2003. These site rankings are made based on a relative scale and range from 1-5, with "1" representing the sites with the highest levels of contamination and risk of human exposure (ECY 2003).

3.2 Regional Economics

The median household income in the city of Yakima is \$41,121, allowing for an average per capita income of \$22,005. These figures are approximately three-fifths of the statewide

averages (\$70,979 and \$36,975 respectively). As such, 16.9% of Yakima residents live below the poverty line. An even more striking statistic from the 2017 U.S. census shows that 30% of children under the age of 18 in Yakima are living below the poverty line. This is more than double the statewide average of 14%. The median value of owner-occupied housing units in the city is \$168,700; just about half of the statewide average of \$339,000 (U.S. Census 2017). The home ownership rate in Yakima is 62.8%, which is only slightly lower than the national average of 63.6% (Federal Reserve 2018).

As of 2016, the most common industries of employment in Yakima, Washington were healthcare and social assistance (14.4% of total employment), agriculture (11.9%), and retail trade (11.7%) (U.S. Census 2017). In Yakima County overall, agriculture constitutes 27.5% of total employment (health services constitute the second largest share at only 14.5%); with the growing, harvesting, shipping, and processing of deciduous tree fruits such as apples, pears, and cherries forming the backbone of the economy (USDA n.d.). This highlights the historical importance of agriculture for Yakima, which is the #1 county in the nation for apple production, and the #1 county in Washington in terms of total crop market value (USDA 2012).

As methods for agricultural production have become more efficient over time, the number of orchards in Yakima County has been steadily decreasing despite increases in total fruit output. From 2007 to 2011, the total number of farms in Yakima County decreased by 11% from 3,540 to 3,143 while the market value of products sold increased from approximately \$1.2 billion to \$1.6 billion (USDA 2012). As the number of farms has decreased, the amount of lead-arsenate contaminated former orchardland available for residential and commercial development has increased. Given that there is no legislation forcing developers to disclose or even test for the

presence of lead-arsenate contaminated soil, cities such as Yakima continue to expand out into former orchards once heavily sprayed with lead-arsenate pesticides (Schick and Flatt 2015).

The map figures included detail the extent of this expansion. Figure 1.1 displays a set of geo-referenced airphotos which were flown over the city of Yakima in 1927. These airphotos were flown during the height of lead-arsenate pesticide application in Yakima and clearly display the density of orchards (which are easily identifiable as uniform rows of cultivated trees) surrounding the city center circa 1920.

The set of 1927 aerial photos has been provided courtesy of Jennifer Hackett, owner of the GIS firm Manastash Mapping, which provides GIS services to communities in Kittitas County and the Yakima River Basin. Using historic landmarks, like bridges, churches, and fairgrounds, we have georeferenced these airphotos with a maximum offset error of no more than 5 meters at any given point so that they could be overlaid accurately on top of current-day aerial photography depicting Yakima, Washington.

Figure 1.2 further illustrates the expansion of Yakima's residential areas into former orchardlands. For this map, the 1927 orchardlands identified in Figure 1.1 have been traced and digitized into semi-transparent polygons, or map shapes. These transparent polygons can now be used to visualize just how much development has occurred on top of likely contaminated former orchardlands in Yakima, Washington. This map reveals a surprising statistic: of the 12,521 recorded and geolocated home sales which have occurred between 2003 and 2018 within the 1927 airphoto extent, 30.66% have involved properties which were being used as orchards in 1927.

Figure 1.1: Georeferenced 1927 Aerial Photography Flown Over Yakima

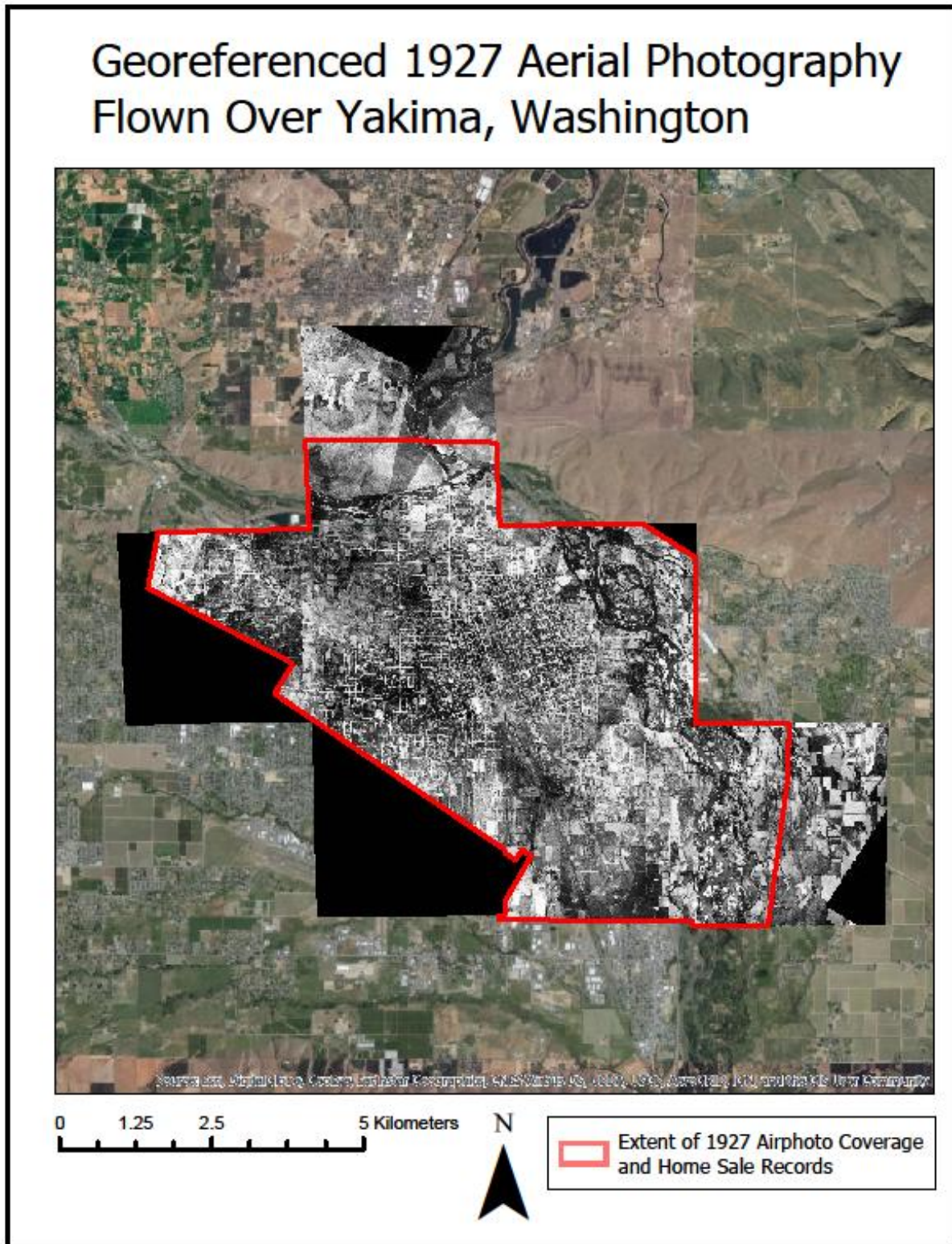
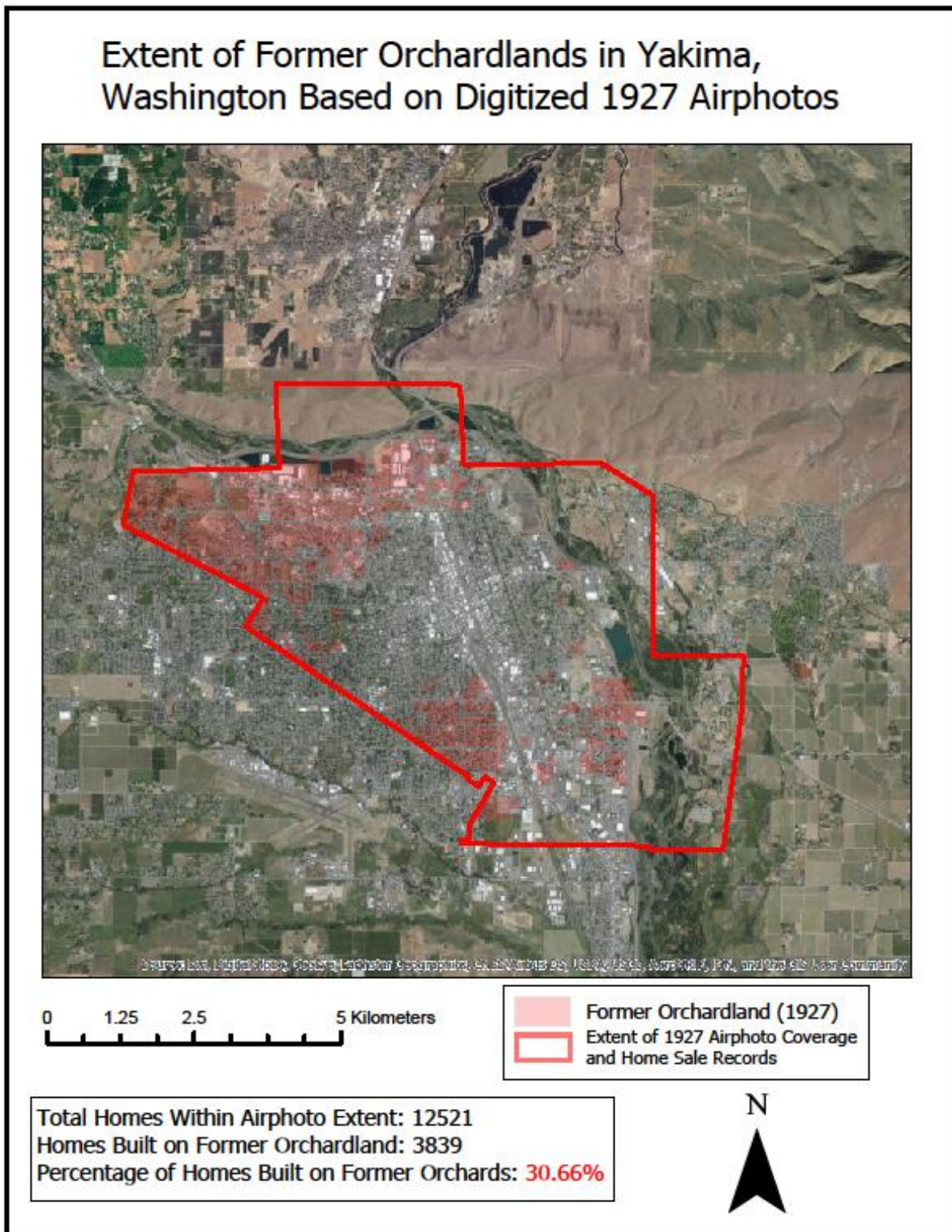


Figure 1.2: Extent of Former Orchardlands in Yakima Washington (1927)



3.3 Yakima School District

Within the Yakima School District (YSD) are 13 elementary schools, 5 middle schools, 3 high schools and 1 technical school. As of May 2017, 16,217 students were attending schools within the YSD. Of those 16,217 students, 78% identified as Hispanic or Latino; 17.3% identified as White or Caucasian; and 2.5% identified as mixed ethnicity. 72.1% of all students attending schools in the YSD are enrolled in free or reduced lunch programs. As Table 1 shows based on key 2016 performance indicators published by the Washington State Office of the Superintendent of Public Instruction, the YSD is lagging behind the rest of the state in graduation rates and standardized testing while displaying much higher chronic absenteeism and discipline rates (OSPI 2016).

Table 1: Key 2016 Performance Indicators for YSD Compared to WA State

Indicator	Washington State	YSD	Difference
Chronic Absenteeism	16.7%	24.2%	169%
Discipline Rate	3.5%	5.7%	161.4%
Graduation Rate	78.1%	65.3%	-12.8%
5 th Grade English Language Achievement (% Meeting Standards)	60.1%	39.6%	-20.5%
5 th Grade Math Achievement (% Meeting Standards)	49.2%	30.3%	-18.9%
5 th Grade Science Achievement (% Meeting Standards)	65.3%	42.3%	-23%

3.4 Lead-Arsenate Cleanup Sites

This study will be centered on the 6 elementary schools within the city of Yakima, Washington which underwent remediation following soil testing conducted in 2005-06 by the Department of Ecology. Each of these locations were found to have soil lead or arsenic concentrations at least in excess of Washington State’s minimum safe thresholds of 250ppm for lead and 20ppm for arsenic contamination. Interim actions to clean up these sites were taken and completed between 2009 and 2012 with the remediated sites either designated “NFA” (no further action needed) or slated for periodic monitoring to ensure that the contaminated soil remains contained below the remediated surface layer (ECY 2012). Table 2 details the exact levels of lead and arsenic which were revealed at each school site by Department of Ecology testing along with the cleanup durations and interim cleanup outcomes achieved at each site.

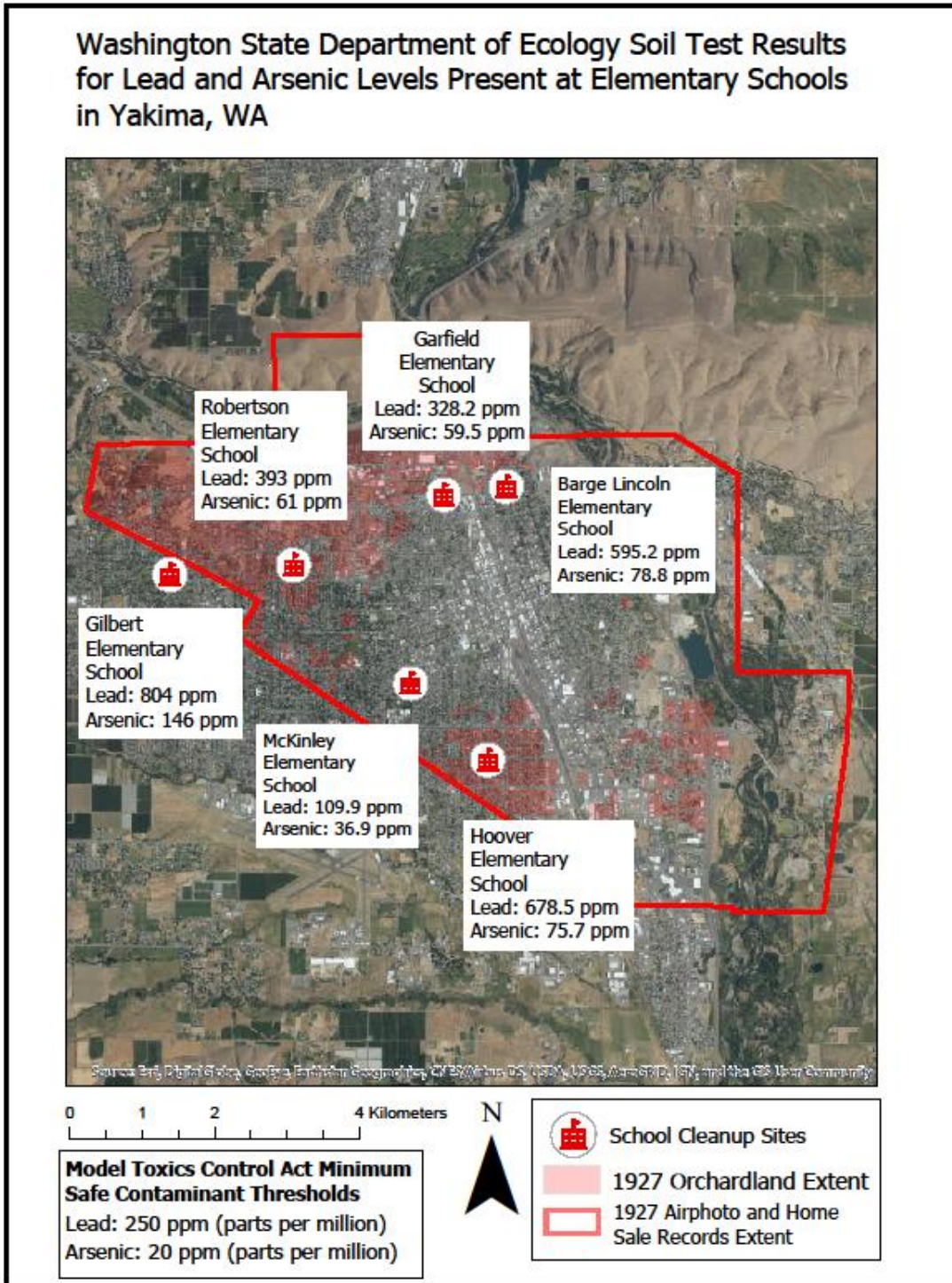
Table 2: Lead-Arsenate Testing Results at Yakima School Sites

Site Name	Cleanup Duration	Lead Levels	Arsenic Levels	Site Status
Hoover Elementary School	151 Days	678.5 ppm	75.7 ppm	CC-Perf. Monitoring
McKinley Elementary School	151 Days	109.9 ppm	36.9 ppm	CC-Perf. Monitoring
Barge Lincoln Elementary School	151 Days	595.2 ppm	78.8 ppm	CC-Perf. Monitoring
Garfield Elementary School	151 Days	328.2 ppm	59.5 ppm	CC-Perf. Monitoring
Gilbert Elementary School	212 Days	804 ppm	146 ppm	NFA
Robertson Elementary School	212 Days	393 ppm	61 ppm	NFA

Additionally included is map Figure 2. Figure 2 depicts the physical locations of each elementary school and reports the lead and arsenic levels found at each site. This map also

includes the overlay of digitized 1927 orchardlands to show how unsafe levels of lead and arsenic at school sites can be spatially correlated with the presence of these former orchardlands.

Figure 2: Lead-Arsenate Cleanup Sites in Yakima, Washington



3.5 Yakima County Soils

The soils found below the remediation sites are characterized as primarily Cowiche loam, Harwood loam, Ashue loam, Willis silt loam, Ritzville silt loam, Naches loam, Warden silt loam, and Esquatzel silt loam. These coarse and silt-loamy soils all have a pH range of between 7 and 7.8, indicating neutral and slightly alkaline soils which lend themselves well to the exchange of cation ions (NRCS 2007). A study conducted by Zimdahl and Skogerboe (1977) found that these “superactive” soils with a high capacity for cation ion exchange have higher rates of lead absorption and immobilization. This allows for high concentrations of lead contamination to become trapped and remain in the surface and near-surface layers of soil (Zimdahl and Skogerboe 1977).

CHAPTER IV

DATA COLLECTION AND VARIABLE CREATION

4.1 Housing Data

In order to conduct the regression analysis outlined in this study, housing data for the city of Yakima, Washington first had to be collected and cleaned so that key regression variables could be created. The Yakima County Assessor's office provided a raw dataset containing 60,290 home sale records. These records detail the selling price of each single-family home in Yakima along with the physical attributes and structural features of those homes. Home sale price serves as the dependent variable in our regression models, while structural features and neighborhood characteristics are utilized in the models as independent variables. The dataset contains records dating from 2003 to 2018. This date range is sufficient for use in evaluating the economic impacts of Yakima's school site brownfield remediations given that the first remediations were announced and listed by the Washington State DOE in 2006, and the last of the physical cleanups were completed in 2012. The entire remediation period is therefore encompassed within the sample of home sale records employed in this study. A significant amount of data cleaning was undertaken before this home sale data could be used for regression analysis.

The home sales dataset was first filtered to contain only residential home sale records. Studies such as those published by Mihaescu (2010) and Gamper-Rambindran and Timmins (2013) have demonstrated that residential property values are the most heavily impacted by the presence of nearby brownfield contamination given that individuals tend to care most about negative environmental externalities which lie in close proximity to their homes. The residential home sales dataset was then further filtered to remove outlier home sale values. A number of

property inheritance transactions were included in the dataset. These transactions reported sale values which were abnormally low for the sizes and characteristics of the associated properties. As these transactions represented inheritances and not actual sale transactions which could be used in regression analysis to identify the implicit values placed on brownfield remediation; all inheritance transactions were removed from the dataset (Palmquist 1988). Additional outliers in the home sales data were removed based on the interquartile range test ($Q3 + 1.5IQR$ and $Q1 - 1.5IQR$). We calculated the upper boundary for square footage outliers to be a value of 2,896.5. All home sale records reporting square footage values greater than 2,896.5 have been excluded from this study's analysis. Further outlier testing was conducted using the Mahalanobis Distance method to identify observations with outlier values for the key home characteristic variables. The Mahalanobis Distance test identified 409 outliers in the dataset at a 99.9% confidence level. We have subsequently dropped these outliers from the dataset.

The next step in preparing this home sales data for regression analysis involved assigning spatial attributes to each home sale record. In order to determine the impact of brownfield remediation on nearby home sale values, information detailing each home sale record's spatial location would be needed. Geographic information service (GIS) techniques were required to assign spatial information to each home sale record. The primary technique employed here is known as "geocoding", wherein GIS software is used to take the ZIP code and street address listed for each sale record and place a point corresponding to each address onto an existing basemap of Yakima, Washington's streets and neighborhoods. This process proved initially problematic however, as the original home sales dataset contained only the street address for each sale record without the associated ZIP code. Based solely on this address information, the GIS software was able to match most of the home sale records with a physical location on the

Yakima map, however, given that the home sales dataset contained records from all across Yakima County, many records were initially unable to be placed on the map with certainty. These “tied” records, as they are referred to in the GIS software, were common addresses which may exist simultaneously in multiple ZIP codes within Yakima County. Common street names such as “First Street” or “Second Avenue” were particularly problematic, as many different municipalities within the county had streets sharing these names which were indistinguishable from one another by the geocoding software in the absence of ZIP code data.

The first attempt at geocoding without ZIP codes returned an inadequately low match rate. The geocoding software was able to correctly place 54,417 home sale records onto the map leaving 5,873 “tied” records, the omission of which could have introduced significant bias to our regression results. We were able to overcome this obstacle by finding that each home sale record in the dataset is labelled with the township, range, and section number associated with that property. The township, range, and section (TRS) system divides the United States into a uniform grid pattern. By applying a GIS layer displaying this grid to our study area map, we were able to manually verify the location of each “tied” home sale record by selecting (from a list of potential locations) the location which fell within the correct TRS grid and which received the highest geocoder accuracy score. This manual verification allowed us to reduce the number of tied records countywide from 5,873 to 597. These final 597 tied records were missing both TRS grid numbers and ZIP codes and would have to be excluded from our regression analysis.

This process of data cleaning and geocoding left us with a list of 18,757 residential home sales which occurred within Yakima city limits between 2003 and 2018. These geocoded home sale records were then spatially joined with a 2010 U.S. Census block group dataset so that variables relating to neighborhood attributes could be included in our models, and spatial

autocorrelation could be controlled for. In order to account for and control for the effects of annual price inflation and fluctuations in the local real estate market, we applied a real sale price adjustment to our home sale prices based on the St. Louis Federal Reserve’s (FRED) 20 City Composite Home Price Index. Through this adjustment, we converted the sale prices provided in our home sales dataset into “real” sale prices with a base year of 2012. We also generated real sale price variables utilizing the FRED’s Washington State Home Price and Yakima Regional Home Price Indices, however, the use of real sale price variables created with these alternative indices did not substantially impact our regression results. For this reason, we have chosen to utilize only the real sale prices generated from the 20 City Composite Home Price Index for the analysis which follows (S&P Global 2020).

Table 3 reports some summary statistics from our cleaned home sales data. This is the dataset which we would use in our regression analysis to identify the impact that the Yakima school site remediations have had on property values within affected school districts.

Table 3: Summary Statistics for Yakima Home Sales Dataset 2003-2018 (n=18757)

Variable	Mean	Std. Dev.	Min Value	Max Value
Sale Price (\$2012)	134,584.93	86,550.99	7,685.84	2,175,000.00
Floor Area (sq.ft)	1,500.05	611.44	238.00	2,896.50
Bedrooms	2.93	0.82	1.00	10.00
Acres	0.35	0.80	0.01	56.45
Age (years)	54.75	31.05	1.00	138.00

From this home sales data, we have also generated a subset of home sale records which fell within the boundaries of our georeferenced 1927 aerial photography polygons. This subset of data would be used in a preliminary regression model intended to gauge the degree of local awareness regarding the areawide soil contamination associated with the former orchardlands.

Summary statistics for this data subset can be found in Table 4. The key variable to note in this data subset is listed as “In_Orchard_1927”. This binary variable reports whether or not a given home was built on a parcel of contaminated former orchardland, as identified in Figure 1.2.

Table 4: Summary Statistics for Subset of Home Sales (2003-2018) Occurring Within 1927 Airphoto Extent (n=11422)

Variable	Mean	Std. Dev.	Min Value	Max Value
Sale Price (\$2012)	82,197.25	57,637.38	0.6954064	305,000
In_Orchard_1927	0.3090527	0.4621232	0	1
Floor Area (sq. ft)	1,163.034	430.6471	208	2,891
Bedrooms	2.559272	0.7855278	1	4
Age (years)	68.92226	26.90787	0	138

4.2 School Cleanup Data

Within our study area of Yakima, Washington, remediations for lead-arsenate soil removal occurred at 6 of Yakima’s 13 total elementary schools. The physical remediations took place between 2009 and 2010, with some school sites added to the U.S. EPA’s National Priorities List (NPL) as early as 2006 following the initial soil tests undertaken. Table 5 lists the Yakima area schools which received remediations along with some temporal data pertaining to the remediation timelines for each cleanup site. This data has been provided by the Washington State Department of Ecology.

Table 5: School Site Cleanup Timelines

Site Name	Cleanup Start Date	Cleanup End Date	Site NPL Listing Date	Site NPL Delisting Date
Hoover Elementary School	4/1/2010	8/30/2010	1/3/2007	Not Delisted
McKinley Elementary School	4/1/2010	8/30/2010	1/3/2007	Not Delisted
Barge Lincoln Elementary School	4/1/2010	8/30/2010	1/3/2007	Not Delisted
Garfield Elementary School	4/1/2010	8/30/2010	1/3/2007	Not Delisted
Gilbert Elementary School	6/1/2009	12/30/2009	8/22/2006	8/18/2010
Robertson Elementary School	6/1/2009	12/30/2009	8/22/2006	8/18/2010

As this table displays, four of the six remediated schools were placed on the NPL for known contaminated sites; however, only two of these four schools were ever delisted from the NPL. The sites which remain listed received an EPA designation of “Performance Monitoring” following the remediations which occurred there. This designation mandates periodic reviews to be undertaken at the remediation sites to ensure that the contaminated soils found therein remain “capped” safely underground below layers of clean topsoil (ECY 2012). In addition to the temporal cleanup data displayed in Table 5, the Department of Ecology has also provided us with publicly available cost figures pertaining to 5 of the 6 school cleanups. These cleanup costs can be seen in Table 6.

Table 6: Remediation Costs for Yakima Elementary School Cleanups

Remediation Costs for Yakima Schools	
School Site	Remediation Cost
Garfield Elementary	\$ 161,060.53
Robertson Elementary	\$ 268,853.26
Hoover Elementary	\$ 284,592.70
Barge-Lincoln Elementary	\$ 206,345.57
Gilbert Elementary ***	Data Not Available
McKinley Elementary	\$ 142,457.61

Unfortunately, cost data for Gilbert Elementary School could not be obtained due to complications stemming from the ongoing COVID-19 viral pandemic. Cost data for the other 5 school sites has been digitized and made available online, however, a clerical error has kept the Gilbert Elementary cleanup cost paperwork from being digitized. Due to a statewide lockdown imposed in response to the COVID-19 pandemic, we are unable to access the Department of Ecology’s physical files which detail cost figures for the Gilbert Elementary school remediation. As such, we have been forced to estimate cleanup costs for this site based on an average of the

costs observed elsewhere in our study area. This estimation will be detailed further in the Methods section.

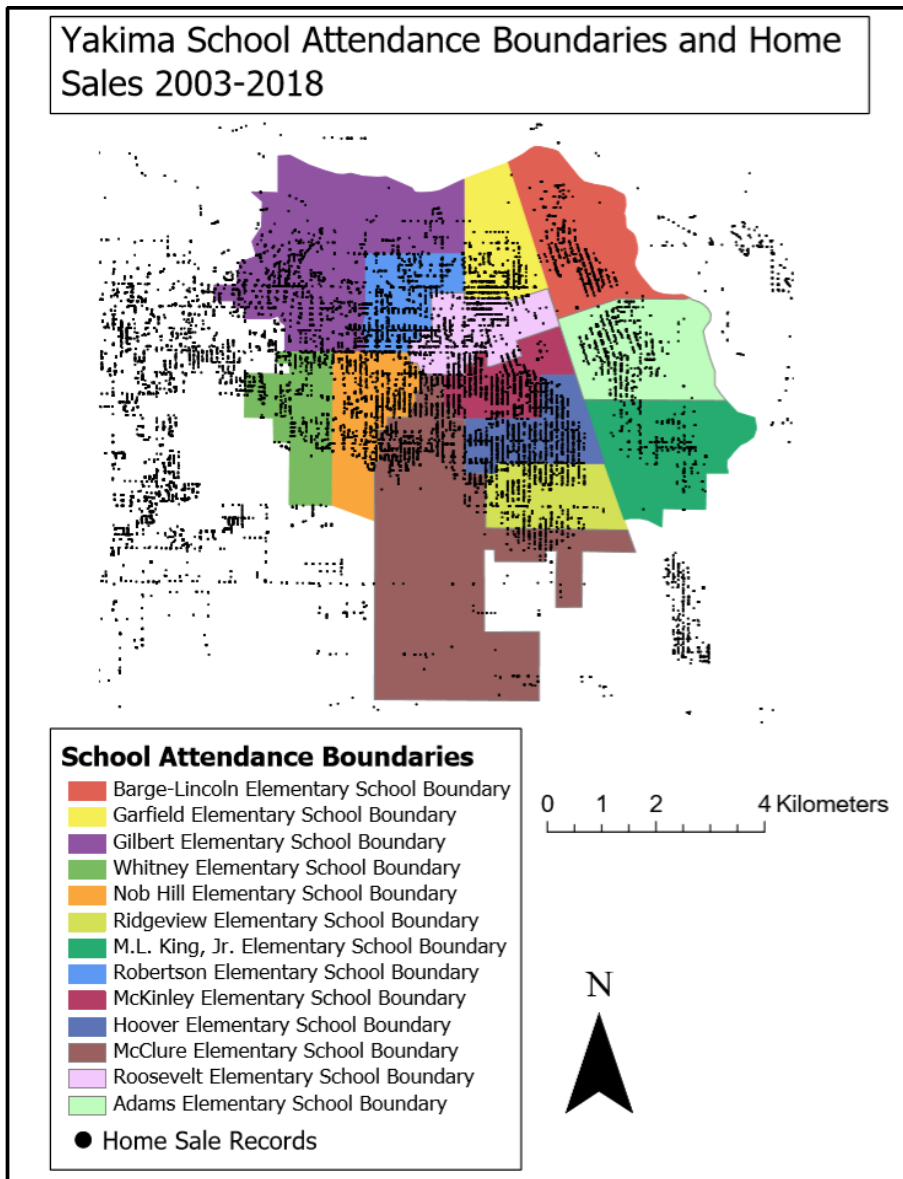
These school remediations will form the basis for the key treatment variables to be used in this study's regression models. Specifically, a given sold property's inclusion in a school district where remediation took place will be used to determine the impact of said remediation on home sale values. According to the Yakima School District's operating procedure #3130; "Students shall attend the school designated for their respective residential, boundary attendance area unless individual requests for transfers have been approved through Central Registration according to district operational procedures" (YSD 2019). This study therefore operates under the assumption that the school a student attends depends on which school district boundary the student's house falls within, and that homebuyers are taking this into account when making the decision to purchase a house within the study area. There is a degree of uncertainty surrounding this assumption, as individual transfer requests do allow students to attend the elementary school of their choice regardless of whether said students live within that school's attendance boundary. Our study therefore must assume that the number of students who have used this transfer request system to attend an elementary school which falls outside of the attendance boundary where they live is small enough that these transfer students would not significantly impact or bias our results.

Prior studies including those conducted by Boyle et al. (2010) and Martin (2017) have found statistically significant correlations between environmental contamination at schools and decreased home sale values within the district boundaries for the contaminated schools. This study, like the aforementioned, therefore relies on the assumption that the negative externality of increased exposure risk to lead-arsenate contamination for children living in the remediated

school districts will be capitalized into the selling prices of homes within the contaminated district boundaries.

The Yakima School District has provided a map of elementary school attendance boundaries for the city of Yakima, Washington. This map has been overlaid onto the previously created map marking the locations of all home sales for the city of Yakima between 2003 and 2018. This map, labelled “Figure 3”, has been included as well.

Figure 3: Yakima School District Boundaries and Home Sales



4.3 Treatment Group Variable Creation

Using the data overlaid onto this map, a GIS spatial join was applied to assign attributes to each home sale record detailing which school district the given sale occurred in. This allowed us to create a set of 4 treatment groups for homes sold within school district boundaries where remediations occurred. The 4 treatment groups include homes sold in remediated school districts during varying stages of the remediation process. In accordance with the prevailing literature discussed previously, we have created 2 treatment groups for homes sold following the beginning and ending of cleanup activities at each site. Another 2 treatment groups have been created for homes sold following a site's listing and delisting from the NPL.

It has been well documented in the literature discussed previously in this study that the start of cleanup activities at a contaminated site signals to the public that the contamination is both serious and real. These cleanup start dates often trigger positive price effects so long as the general public believe that the cleanups will be effective in removing the hazard. However, if there has been little public awareness of the contamination prior to the cleanups and the public has strong doubts regarding the efficacy of the cleanups, these start dates can trigger negative price effects as individuals become aware of the hazard and begin to capitalize this into their real estate purchasing decisions (Martin 2017; Gampar-Rabindran and Timmins 2013). Prevailing literature also shows that this initial negative price impact is rarely permanent, as a strong price rebound has been demonstrated by prior studies to occur following both the completion of cleanup activities and the delisting of contaminated sites. This is in part because the cleanup completion and site delisting dates send strong signals to potential homebuyers that the problem has been resolved and the hazard no longer exists. If, however, homebuyers believe strongly that the cleanups have not sufficiently addressed the hazard; the cleanup completion date and

delisting date may lead to further negative impacts on home sale prices (Bryson 2012; Gampar-Rabindran and Timmins 2013; Kim et al. 2016).

For this study, we would expect to see results consistent with the prevailing literature. One area of concern regarding the set of “site delisting” treatment groups in our study is that only two of the six remediated schools in Yakima ever received the “no further action” designation necessary for delisting, leading the sample size for these groups to be rather small. This area of concern will be covered further in the Methods and the Discussion sections to follow.

Our four treatment group variables have been measured at both concentric and non-concentric intervals of 6, 12, 18, 24, 30, 36, and 42 months from the initial timeline dates displayed in Table 5 in order to model changes in home sale prices over the remediation projects’ lifespans and to capture any lag in the public response to these remediations (Martin 2017; Boyle et al. 2010). Tables 7 and 8 list these four treatment groups in both concentric and non-concentric form and detail the number of home sale records reported for each time period and treatment group.

Table 7: Treated (Concentric) Residential Home Sale Counts for Remediated Yakima Elementary School Boundary Areas (n=18757)

Variable	0-6 mos	6-12 mos	12-18 mos	18-24 mos	24-30 mos	30-36 mos	36-42 mos
Listed	120	128	104	134	84	115	94
Started	152	92	116	100	128	112	146
Ended	94	110	112	130	107	137	145
Delisted	51	55	45	42	41	63	71

This broad range of treatment groups allows us to measure not only the public’s initial response to the cleanups, but also to identify any long-term effects or lingering negative stigma associated with the remediated districts. These treatment groups serve as a proxy variable for

local environmental quality in our hedonic regression models and will be used to determine home sale price impacts from remediation. The utilization of these groups as regression variables will be described in greater detail in the Methods section.

Table 8: Treated (Non-Concentric) Residential Home Sale Counts for Remediated Yakima Elementary School Boundary Areas (n=18757)

Variable	0-6 mos	0-12 mos	0-18 mos	0-24 mos	0-30 mos	0-36 mos	0-42 mos
Listed	120	248	352	486	570	685	779
Started	152	244	360	460	588	700	846
Ended	94	204	316	446	553	690	835
Delisted	51	106	151	193	234	297	368

CHAPTER V

METHODS

5.1 Hedonic Regression Modelling

As mentioned in the literature reviewed previously, hedonic housing price models containing environmental proxy variables are considered the ‘gold standard’ for determining or uncovering the implicit values that individuals place on environmental amenities such as the remediation of nearby contaminated school sites (Palmquist 1988; Boyle et al. 2010; Mihaescu 2010; Martin 2017; Schwarz et al. 2017). This is due to the fact that these models are capable of controlling for the effects of all factors which traditionally impact home sale prices through the use of detailed home sales datasets and proxy variables representing these factors. When run using a sufficiently robust set of home sales data, hedonic housing price models are able to determine and control for the ways in which home sale prices are affected, on average, by home characteristics such as square footage, acreage, neighborhood location and quality, the home’s age, and the number of bedrooms to name a few. The output from these hedonic regression models will be a coefficient for each modelled variable stating the estimated impact of that variable on home sale prices in the region. The inclusion of proxy variables for environmental quality (whether or not a home is located in a school district contaminated by lead-arsenate pesticide, for example) will allow a hedonic model to estimate how these environmental quality variables tend to impact home sale prices in the study area, since all other factors which may affect home sale prices are already being controlled for in the model (Palmquist 1988; Boyle et al. 2010).

Hedonic regression analysis has been selected as the method of choice for this study over alternative methods like contingent valuation for a few key reasons. Contingent valuation, which

involves directly surveying respondents in a study area to determine the values that they place on contaminated site remediation, is generally less accurate than hedonic regression analysis and would be a preferable method for this study only in the absence of detailed and robust home sales data pertaining to the study area (which makes hedonic regression analysis possible). This is due in part to the errors and biases which may be introduced to a study when directly surveying human subjects. “Hypothetical bias” represents one such example and has been well established as an area of concern in contingent valuation literature. This bias arises due to the fact that contingent valuation survey questions are based on hypothetical scenarios rather than the actual purchasing behavior analyzed by hedonic regression models. It has been widely accepted in contingent valuation literature that hypothetical questions often receive hypothetical responses from surveyed individuals. Since it is difficult for individuals to answer such hypothetical questions accurately, survey responses often do not reflect the individual’s true willingness to pay (values) for the removal of a given environmental disamenity (Venkatachalam 2004).

Contingent valuation methods are also vulnerable to biases introduced during the administering of surveys to the general public, as results can be heavily skewed if the sample of survey responses is not representative of the population demographics found in the study area (Venkatachalam 2004). For example, if a survey written exclusively in English was distributed to a study area with a majority Spanish-speaking population, the survey responses would likely represent a biased or skewed sample of respondents. Due to the availability of robust home sales and school site cleanup datasets, we have chosen to employ the more straightforward hedonic regression analysis method in this study, thus avoiding the potential biases and difficulties associated with contingent valuation. This hedonic analysis method allows us to determine the

implicit impact that school site remediations have had on nearby home sale prices and to use this impact as a proxy for the value that individuals place on improved local environmental quality (the removal of hazardous lead-arsenate contamination from nearby schools).

The hedonic housing price regressions that we have chosen to run in this study can be thought of as a hybrid of pooled and panel data models. This is because we have both unique, one-time home sale records (representing pooled data) in addition to some repeat home sale records occurring at different points in time (representing panel data) within the study area of Yakima, Washington. These are all considered fixed effects models, as we include census block group fixed effect variables in our models in order to control for unobservable spatial housing attributes which may affect sale prices and thus avoid introducing omitted variable bias into our models and results (Guignet 2013; Kim et al. 2016; Martin 2017). The inclusion of census block group factor variables also helps to control for spatial autocorrelation, which is a phenomenon wherein residential property values tend to be correlated with or dependent upon the values of other nearby properties. Additionally, we have run all of our regression models with Stata default HC1 robust standard errors.

We will be running log-linear regressions for this study; meaning that our models will utilize the natural log of real property sale prices as the dependent variable. There is a general consensus in hedonic modelling literature regarding the ability of log-linear regression models to control for the high degrees of variation commonly found in housing price datasets (Boyle et al. 2010; Mihaescu 2010; Schwarz et al. 2017). By controlling for this extreme variance, log-linear regression models are able to address any heteroscedasticity present in the data.

Before running our primary regression equations, we wanted to gauge the degree of local homebuyer awareness with regards to the presence of area-wide lead arsenate contamination in

Yakima. This was accomplished through the use of a preliminary regression model and the subset of home sales data described in Table 5 of the Data Collection section. This preliminary model took on the following conceptual form:

$$\ln(P) = f(C,N,O)$$

where $\ln(P)$ represents the natural log of real home sale prices (converted to 2012 dollars using the Case-Shiller 20 City Composite U.S. Home Price Index provided by the U.S. Federal Reserve); C represents a vector of house and property-specific characteristics (for example: square footage and age among others); N represents a vector of neighborhood-specific characteristics which may affect home values (as captured and controlled for by the census block group variable); and O represents a binary variable which describes whether or not the home in question was built on top of contaminated former orchardlands.

The conceptual form of our primary regression equation can be described as follows:

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

where $\ln(P)$ represents the natural log of real home sale prices (converted to 2012 dollars using the Case-Shiller 20 City Composite U.S. Home Price Index provided by the U.S. Federal Reserve); C represents a vector of house and property-specific characteristics (for example: square footage and age among others); N represents a vector of neighborhood-specific characteristics which may affect home values (as captured and controlled for by the census block group variable); and E represents a proxy variable for environmental quality (in this case, whether a given home sale occurred within one of the contaminated schools' attendance boundaries and when that sale occurred relative to the remediation timeline at the

aforementioned contaminated school). This conceptual form is expanded upon in the functional forms detailed below.

For the functional forms of our regressions, the interpretations for variables C, N, O, and E remain consistent with the conceptual form explained previously. As such, the term β_x found in the functional forms below represents the modelled coefficient estimates for our housing characteristics which include square footage, age, acreage, number of bedrooms, and building quality. For all forms, the term δ represents the Census block group fixed effects which control for neighborhood-specific characteristics (N in the conceptual form above) while the term λ represents temporal fixed effects (indexed and controlled for by month and year). The term β_y represents the coefficient estimates for our environmental proxy variables which have been listed and detailed in Table 6 and Table 7. The idiosyncratic error term in our models below is represented by the term ε . The subscripts i, j, and t are included in the functional forms below to denote whether each variable is affected by individual house observation, block group, or point in time, respectively.

Preliminary Form – Modelling ONLY the price impact of a home being constructed on former orchardlands

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \beta_y O_{ij} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

As previously mentioned, this preliminary regression form is intended to gauge local awareness of the area-wide lead-arsenate contamination hazard. If the model returned a statistically or economically insignificant β_y coefficient value (representing the price impact of a home being built on former orchardlands), this would suggest a low degree of local awareness regarding the hazard as individuals are not capitalizing its presence into their purchasing decisions. If there is a

high degree of awareness regarding this hazard among Yakima homebuyers, we would then expect to see a statistically significant negative coefficient value for β_y .

Form A – Concentric treatment variables for ONLY the start of cleanup activities at each school site grouped in 6-month intervals

(0-6 months after start, 6-12 months after start, 12-18 months after start, ... , 36-42 months after start)

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \sum \beta_y E_{ijt} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Form A is intended to determine the public’s reaction to the start of cleanup activities at school sites in Yakima. The concentric treatment variables are also employed here to measure how quickly local homebuyers capitalized the signals given by the start of cleanup activities into their purchasing decisions. These concentric treatment groups will reveal which time lag (6 months, 9 months, ... , 42 months) yields the most significant impacts on sale price for “cleanup start” treatments.

Form B – Concentric treatment variables for ONLY the NPL listing date of each school site grouped in 6-month intervals

(0-6 months after listing, 6-12 months after listing, 12-18 months after listing, ... , 36-42 months after listing)

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \sum \beta_y E_{ijt} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Form B is intended to determine the public’s reaction to the listing of school sites in Yakima to the NPL register of contaminated sites. The concentric treatment variables are again employed here to measure how quickly local homebuyers capitalized the information revealed by the initial NPL listing of the contaminated schools into their purchasing decisions. These concentric

treatment groups will reveal which time lag (6 months, 9 months, ... , 42 months) yields the most significant impacts on sale price for “site listing” treatments.

Form C – Concentric treatment variables for ONLY the end of cleanup activities at each school site grouped in 6-month intervals

(0-6 months after end, 6-12 months after end, 12-18 months after end, ... , 36-42 months after end)

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \sum \beta_y E_{ijt} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Form C is intended to determine the public’s reaction to the conclusion of cleanup activities at contaminated school sites in Yakima. The concentric treatment variables are again employed here to measure how quickly local homebuyers capitalized the signals sent by the termination of cleanup activities and ensuing re-opening of previously contaminated schools into their purchasing decisions. These concentric treatment groups will reveal which time lag (6 months, 9 months, ... , 42 months) yields the most significant impacts on sale price for “cleanup end” treatments.

Form D – Concentric treatment variables for ONLY the NPL de-listing date for each school site grouped in 6-month intervals

(0-6 months after de-listing, 6-12 months after de-listing, 12-18 months after de-listing, ... , 36-42 months after de-listing)

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \sum \beta_y E_{ijt} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Form D is intended to determine the public’s reaction to the de-listing of each affected school site in Yakima from the NPL register of contaminated sites. The concentric treatment variables are again employed here to measure how quickly local homebuyers capitalized the signals sent by the de-listing of each formerly contaminated school site into their purchasing decisions. These

concentric treatment groups will reveal which time lag (6 months, 9 months, ... , 42 months) yields the most significant impacts on sale price for “site de-listing” treatments.

Form E – ALL concentric treatment variables included in a single regression and grouped in 6-month intervals

(0-6 months, 6-12 months, 12-18 months, ... , 36-42 months)

$$\text{Ln}(P)_{ijt} = \sum \beta_x C_{ijt} + \sum \beta_y E_{ijt} + \delta_j + \lambda_t + \varepsilon_{ijt}$$

Form E includes all of the treatment variables which have been regressed separately in forms A through D. This form’s concentric treatment variables will reveal how each successive stage of the remediation process (listing → start → end →de-listing) impacted homebuyers’ purchasing decisions. These concentric treatment groups will reveal which time lag (6 months, 9 months, ... , 42 months) yields the most significant impacts on sale price across treatments while also showing how those impacts change over time.

5.2 Cost-benefit Analysis

Using the findings from our regression modeling, we have conducted a cost-benefit analysis to determine the level of net cost or benefit associated with the six school-site remediations examined in this study. There are two components of the benefit calculations in our cost-benefit analysis: increased tax revenue from home sales and the estimated healthcare costs which were avoided by students who have attended the remediated schools following the cleanups. The “cost” element of our cost-benefit analysis has been taken directly from the Washington State Department of Ecology’s cleanup site details reports which contain detailed totals of the cleanup expenditures at each remediated school site in Yakima. These costs can be found in Table 9. As noted in the “Data Collection and Variable Creation” section, we were unable to access the cleanup cost data for Gilbert Elementary School. To overcome this data

deficiency, we have chosen to estimate the cleanup cost of Gilbert Elementary based on an average of the cleanup costs observed elsewhere in our study area.

Table 9: Yakima Elementary School Remediation Cost Figures and Cost Estimate for Gilbert Elementary

Remediation Costs for Yakima Schools	
School Site	Remediation Cost
Garfield Elementary	\$ 161,060.53
Robertson Elementary	\$ 268,853.26
Hoover Elementary	\$ 284,592.70
Barge-Lincoln Elementary	\$ 206,345.57
Gilbert Elementary ***	\$ 212,661.93
McKinley Elementary	\$ 142,457.61
Total Cost:	\$ 1,275,971.60

Since our findings in the regression results section suggest that home sale prices are impacted negatively as the remediations start and positively after the site in question is delisted from the NPL register of contaminated sites, the tax revenue benefit calculations have been simplified by estimating only the benefits accrued in two years following the delisting of each school site. As shown in Table 14 of the Results section, the delisting treatment “18-24 months after delist” is estimating an average price increase of approximately 10.4% for houses which sold 1.5-2 years following the delisting of the fully remediated schools. It is important to reiterate here that only 2 of the 6 schools in our study area received this delisting treatment, as this will limit the number of home sales to which the price increase of 10.4% may be applied. We have chosen to use this 10.4% price increase figure as it is consistent across model specifications and also has the highest degree of statistical significance out of all the delisting treatments.

In Table 10, we have summed up the real sale prices of all homes which fell within the delisted school attendance boundaries and which sold within 2 years of the delisting. Since our results suggest that the price increases associated with the delisting are not permanent, we have only calculated benefits for this two-year period wherein the “delisting treatment” price increases were observed. This sum of real sale prices will be referred to as “True Sales”, given that this figure represents the actual sale prices of homes in the area including the 10.4% price increase due to the delisting. This figure would be compared with our estimated “Adjusted Sales” figure, which is representative of the hypothetical total value of home sales for this region and time period if the delisting never occurred. Subtracting our “Adjusted Sales” from the “True Sales” would then allow us to estimate the total increase in home sale prices associated with the remediations (and more specifically, the delisting treatments). By applying the city of Yakima’s 2010-2012 average property tax rate of 1.21% (taken from the 2-year period relevant to the delisting treatments) to our “Adjusted Sales” figure, we were able to estimate an “Adjusted Tax” total. This “Adjusted Tax” total could next be compared with the “Real Tax” total, which we have calculated in the same way by multiplying the average tax rate together with the “Real Sales” total. The difference between our “Real” and “Adjusted” tax totals is representative of the total tax revenue benefit accrued in our study area due to increased home sale values stemming from the delisting of remediated schools.

The second component of our benefit calculations involves applying a benefit-transfer from the work of Pichery et al. (2011), which determined that children exposed to lead levels consistent with those observed at the contaminated Yakima school sites would see increased lifetime healthcare costs of approximately \$3,304.79. In order to generate a rough estimate of the healthcare costs which were avoided by children who have attended these formerly contaminated

schools in the years following the remediation, we have multiplied these estimated savings of \$3,304.79 per child to the total number of children who have reportedly attended the remediated schools during the decade in between the remediation end dates (2010) and the present day (2020). This figure (detailed in Table 11) makes up the second component of our total benefit estimation. As Table 11 displays, attendance data for Yakima Elementary schools was only available dating back to the 2014-15 school year. These data were an excellent fit for our analysis, as elementary students who were in 5th grade as of 2015 would have been starting as 1st graders in 2010. Since the school site remediations were all completed before the 2010 school year began; that year's first grade class represents the first generation of Yakima elementary school students who avoided exposure to lead-arsenate as a result of the cleanups. We have therefore counted the elementary schools' total attendance as of the 2014-15 school year to accrue health benefits from the remediations dating back to 2010. For the years following the 2014-15 school year, we have estimated additional health benefits based on each successive year's incoming 1st grade class of new students who are avoiding lead-arsenate exposure by attending the remediated schools. In order to determine the total net cost or benefit associated with these remediations, we have summed together the two components of total benefit and subtracted our total cost figure from that total. These totals can be found at the end of the results section.

Table 10: Tax Benefit Calculations for Cost-Benefit Analysis

Cost-Benefit Analysis: Tax and Revenue Benefit Component Calculations					
True Sales	Adjusted Sales	(Difference)	True Tax	Adjusted Tax	(Difference)
	\$				
\$ 4,626,321.22	4,145,183.81	\$ 481,137.41	\$ 56,066.39	\$ 50,235.48	\$ 5,830.90
Sum Total of Tax and Seller Revenue Benefits:					\$ 486,968.31

Table 11: Health Benefits for Cost-Benefit Analysis

Cost-Benefit Analysis: Avoided Healthcare Cost Component Calculations				
School	Year	New Students	Annual Healthcare Savings Benefit	
Garfield Elementary	2014-15	402	\$	1,328,525.58
Garfield Elementary	2015-16	55	\$	181,763.45
Garfield Elementary	2016-17	65	\$	214,811.35
Garfield Elementary	2017-18	58	\$	191,677.82
Garfield Elementary	2018-19	61	\$	201,592.19
Garfield Elementary	2019-20	57	\$	188,373.03
Robertson Elementary	2014-15	522	\$	1,725,100.38
Robertson Elementary	2015-16	103	\$	340,393.37
Robertson Elementary	2016-17	92	\$	304,040.68
Robertson Elementary	2017-18	103	\$	340,393.37
Robertson Elementary	2018-19	92	\$	304,040.68
Robertson Elementary	2019-20	92	\$	304,040.68
Hoover Elementary	2014-15	742	\$	2,452,154.18
Hoover Elementary	2015-16	117	\$	386,660.43
Hoover Elementary	2016-17	122	\$	403,184.38
Hoover Elementary	2017-18	120	\$	396,574.80
Hoover Elementary	2018-19	117	\$	386,660.43
Hoover Elementary	2019-20	113	\$	373,441.27
Barge-Lincoln Elementary	2014-15	672	\$	2,220,818.88
Barge-Lincoln Elementary	2015-16	118	\$	389,965.22
Barge-Lincoln Elementary	2016-17	108	\$	356,917.32
Barge-Lincoln Elementary	2017-18	120	\$	396,574.80
Barge-Lincoln Elementary	2018-19	108	\$	356,917.32
Barge-Lincoln Elementary	2019-20	89	\$	294,126.31
Gilbert Elementary	2014-15	560	\$	1,850,682.40
Gilbert Elementary	2015-16	101	\$	333,783.79
Gilbert Elementary	2016-17	93	\$	307,345.47
Gilbert Elementary	2017-18	89	\$	294,126.31
Gilbert Elementary	2018-19	90	\$	297,431.10
Gilbert Elementary	2019-20	93	\$	307,345.47
McKinley Elementary	2014-15	447	\$	1,477,241.13
McKinley Elementary	2015-16	73	\$	241,249.67
McKinley Elementary	2016-17	65	\$	214,811.35
McKinley Elementary	2017-18	71	\$	234,640.09
McKinley Elementary	2018-19	71	\$	234,640.09
McKinley Elementary	2019-20	67	\$	221,420.93
Sum Total of Healthcare Benefits (Accrued from 2010-2020)			\$	20,053,465.72

CHAPTER VI

RESULTS

6.1 Hedonic Analysis Results

The results from our preliminary hedonic regression model can be found in Table 12. The key environmental treatment variable in this model is the binary variable which describes whether or not a given home was built on contaminated former orchardlands.

Table 12: Results for Preliminary Regression Model (Impact of a home being built on former orchardlands)

Preliminary Regression Model Results (Former Orchardland Home Sales)	
VARIABLES	Coefficients
Home Built on 1927 Orchardlands	-0.0221 (0.0470)
Constant	7.102*** (0.219)
Observations	11,422
R-squared	0.740
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

Robust standard errors in parentheses

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

As the results listed in Table 12 show, our preliminary model has estimated that homes built on former orchardlands sell for approximately 2.21% lower values than those which have not been built on this likely contaminated land. This coefficient value has been estimated with a very low degree of statistical significance. These findings suggest that there is a low degree of awareness regarding the presence of areawide lead-arsenate soil contamination among Yakima homebuyers, as there do not appear to be significant negative price impacts for homes built on top of

contaminated former orchardlands. This is likely due at least in part to Washington State's real estate disclosure laws (described in greater detail in the introduction section) which do not require home sellers to test for the presence of soil contamination on their properties.

Our primary hedonic regressions have yielded results which are in some ways consistent with and in other ways a departure from the prevailing literature describing the impacts of contaminated sites on nearby property values. The coefficient estimates from our "individual treatment" models have proven to be fairly consistent with our "all treatments model", as tables 13-17 display. Though magnitude and significance vary to some degree, the signs of our treatment variable coefficients remain fairly consistent across model specifications. Our models showed that the most consistently (economically) significant negative price impacts were associated with the beginning and the end of remediation activities in our study area. The "delisting" treatment was the only treatment of the four modelled to be associated with mostly positive price impacts, though these price increases seemed to be somewhat impermanent. As previously mentioned, the coefficients we observed for our "start" and "delisting" treatments are consistent with the prevailing hedonic literature surrounding contaminated sites. Our study's departure from the prevailing literature occurs due to our "end treatment" coefficients.

While most similar studies saw positive price impacts following the remediation activity end dates in their study areas, our "cleanup end" coefficients are consistently negative. The signs of these coefficients could be attributed to a phenomenon wherein the start of the cleanup functions as a signal to consumers that an environmental hazard is present. The disamenity value of that hazard is then capitalized into the selling prices of nearby homes until a strong signal is sent that the hazard is no longer present. In this scenario, the delisting of fully remediated schools from the NPL register of contaminated sites appears to serve as this clear signal after

which home sale prices rebound. Our study is unique in that only 2 of the 6 schools in our study area were remediated thoroughly enough for this NPL delisting to occur. The remaining four schools were remediated but never received a publicized NPL site delisting which would have sent a strong signal to consumers that the lead-arsenate hazard is no longer a concern. The negative price impacts associated with the cleanup end date in our study may suggest that the lack of an NPL delisting for some sites meant that consumers did not believe the remediations at those sites were sufficient to remove the hazard, thus leading them to continue capitalizing the lead-arsenate hazard into their purchasing decisions long after the remediations had been completed. The signs and magnitudes of these coefficients suggest some interesting implications for remediation policy and contaminated site responses moving forward. These implications will be explored further in the Discussion section.

Included here is Table 13, which displays the results of our “Start Treatment Only” regression. These “start treatment” coefficients have also been displayed in the time-series graph titled “Figure 4”. This graph charts the values of our “start treatment” coefficients over time (marked in red) and also includes a 95% confidence interval for those coefficient estimates (marked in gray). It is important to note that all of the time series graphs included in this section follow this template.

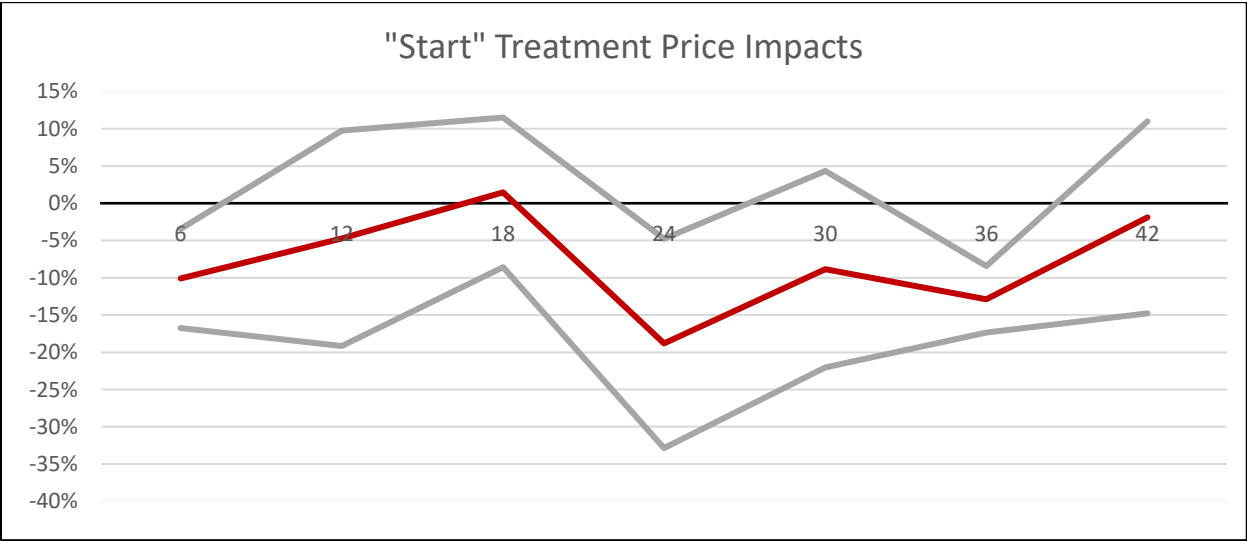
Table 13: Results for Start Treatment Only Regression Model (Form A)

Start Treatment Only Regression Results (Model Form A)	
VARIABLES	Coefficients
Sold 0-6 Months After Cleanup Start	-0.101** (0.0259)
Sold 6-12 Months After Cleanup Start	-0.0472 (0.0562)
Sold 12-18 Months After Cleanup Start	0.0146 (0.0391)

TABLE 13 (CONTINUED)	
VARIABLES	Coefficients
Sold 18-24 Months After Cleanup Start	-0.188**
	(0.0547)
Sold 24-30 Months After Cleanup Start	-0.0885
	(0.0513)
Sold 30-36 Months After Cleanup Start	-0.129***
	(0.0173)
Sold 36-42 Months After Cleanup Start	-0.0188
	(0.0501)
Constant	10.58***
	(0.0786)
Observations	18,757
R-squared	0.403
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

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

Figure 4: Time-series Graph of "Start" Treatment Price Impacts



As this chart and the accompanying graph display, our “cleanup start treatment” regression coefficients were primarily negative, with the most statistically and economically significant impacts (-18.8%) observed 24 months (2 years) after the start of cleanup activities at each school site in our study area. These negative “start treatment” coefficients are indicative of

a low degree of public awareness in our study area regarding the presence of an environmental hazard prior to the cleanups. In the absence of prior knowledge pertaining to the lead-arsenate hazard, these publicized, eye-catching cleanup operations would have acted as the first signal revealing that there is an environmental disamenity in the area which should be factored into property values.

Table 14 and Figure 5 detail the results of our regression model Form B, which employs only the NPL site listing date for each contaminated school site as the key treatment variable.

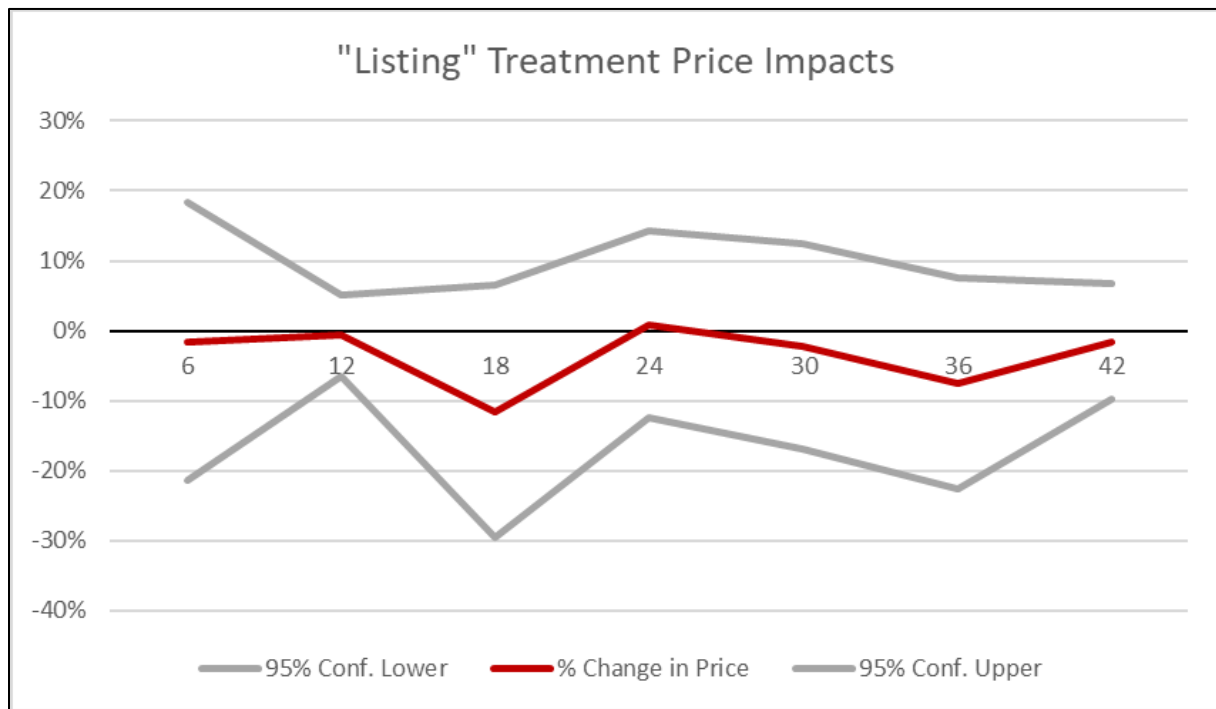
Table 14: Results for Listing Treatment Only Regression Model (Form B)

Listing Treatment Only Regression Results (Model Form B)	
VARIABLES	Coefficients
Sold 0-6 Months After NPL Listing	-0.0145 (0.0777)
Sold 6-12 Months After NPL Listing	-0.00835 (0.0220)
Sold 12-18 Months After NPL Listing	-0.119 (0.0711)
Sold 18-24 Months After NPL Listing	0.00705 (0.0533)
Sold 24-30 Months After NPL Listing	-0.0219 (0.0585)
Sold 30-36 Months After NPL Listing	-0.0829 (0.0605)
Sold 36-42 Months After NPL Listing	-0.0135 (0.0322)
Constant	10.58*** (0.0789)
Observations	18,757
R-squared	0.402
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

Robust standard errors in parentheses

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

Figure 5: Time-series Graph of "Listing" Treatment Price Impacts



As Table 14 and Figure 5 report, the NPL site listing dates appear to have had a generally negative impact on home sale prices in our study area. It should be noted that these impacts are less statistically and economically significant when compared to the results of our “start treatment” model. The most economically significant impact (an 11.9% decrease in home sale prices) was observed after an 18-month (1.5-year) lag period following the listing dates. However, as the 95% confidence interval displayed in Figure 5 and the p-values included in Table 14 suggest, none of the “listing date” coefficients have a high degree of statistical significance. These findings could potentially be explained by a lack of awareness in Yakima regarding the NPL site listings. If a majority of consumers were unaware of the listings, then it stands to reason that the listing date would not have a very strong impact on local property values.

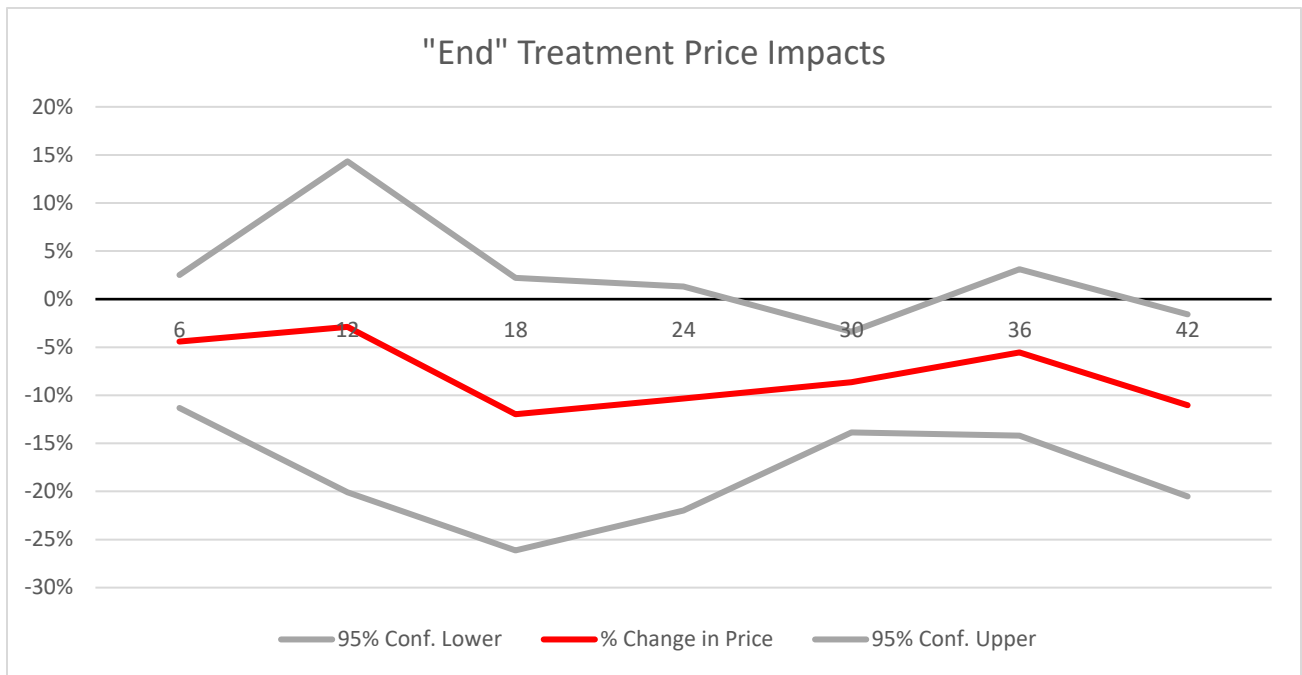
Table 15 and Figure 6 detail the results of our “end treatment” model Form C. This model employs the cleanup end date at each remediated site as the key treatment variable. This date marks the official end of the remediation process at each site, after which the schools would be set to re-open with the lead-arsenate hazard supposedly removed or contained.

Table 15: Results for Cleanup End Treatment Only Regression Model (Form C)

Ending Treatment Only Regression Results (Model Form C)	
VARIABLES	Coefficients
Sold 0-6 Months After Cleanup End	-0.0440 (0.0269)
Sold 6-12 Months After Cleanup End	-0.0288 (0.0670)
Sold 12-18 Months After Cleanup End	-0.120* (0.0551)
Sold 18-24 Months After Cleanup End	-0.103* (0.0453)
Sold 24-30 Months After Cleanup End	-0.0863*** (0.0204)
Sold 30-36 Months After Cleanup End	-0.0553 (0.0337)
Sold 36-42 Months After Cleanup End	-0.110** (0.0368)
Constant	10.58*** (0.0780)
Observations	18,757
R-squared	0.403
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

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

Figure 6: Time-series Graph of "Ending" Treatment Price Impacts



As the results display; the coefficient estimates for our “end treatment” variables were all negative with high degrees of both statistical and economic significance (relative to our other treatment groups). These findings differed from those observed in much of the literature reviewed above, as those studies typically found the remediation end date to be correlated with increased home sale prices. It has been generally agreed upon in this literature that negative “end treatment” coefficients (such as the ones seen here) may suggest that local homebuyers did not perceive the remediations as having adequately addressed or removed the hazard in question. These findings and their potential interpretations will be covered at greater lengths in the Discussion section.

Table 16 and Figure 7 contain the results of our “delisting treatment” only model Form D. The key treatment variable in this model is the NPL site delisting date, which occurs only after a fully remediated site receives the designation of “No Further Action” (NFA) from the Department of Ecology.

Table 16: Results for Delisting Treatment Only Regression Model (Form D)

Delisting Treatment Only Regression Results (Model Form D)	
VARIABLES	Coefficients
Sold 0-6 Months After NPL Delisting	0.0328 (0.112)
Sold 6-12 Months After NPL Delisting	0.0179 (0.0642)
Sold 12-18 Months After NPL Delisting	-0.0550 (0.0762)
Sold 18-24 Months After NPL Delisting	0.104* (0.0511)
Sold 24-30 Months After NPL Delisting	0.0818 (0.0880)
Sold 30-36 Months After NPL Delisting	0.0393 (0.0214)
Sold 36-42 Months After NPL Delisting	-0.00926 (0.0629)
Constant	10.58*** (0.0789)
Observations	18,757
R-squared	0.402
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

Robust standard errors in parentheses

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

Figure 7: Time-series Graph of "Delisting" Treatment Price Impacts

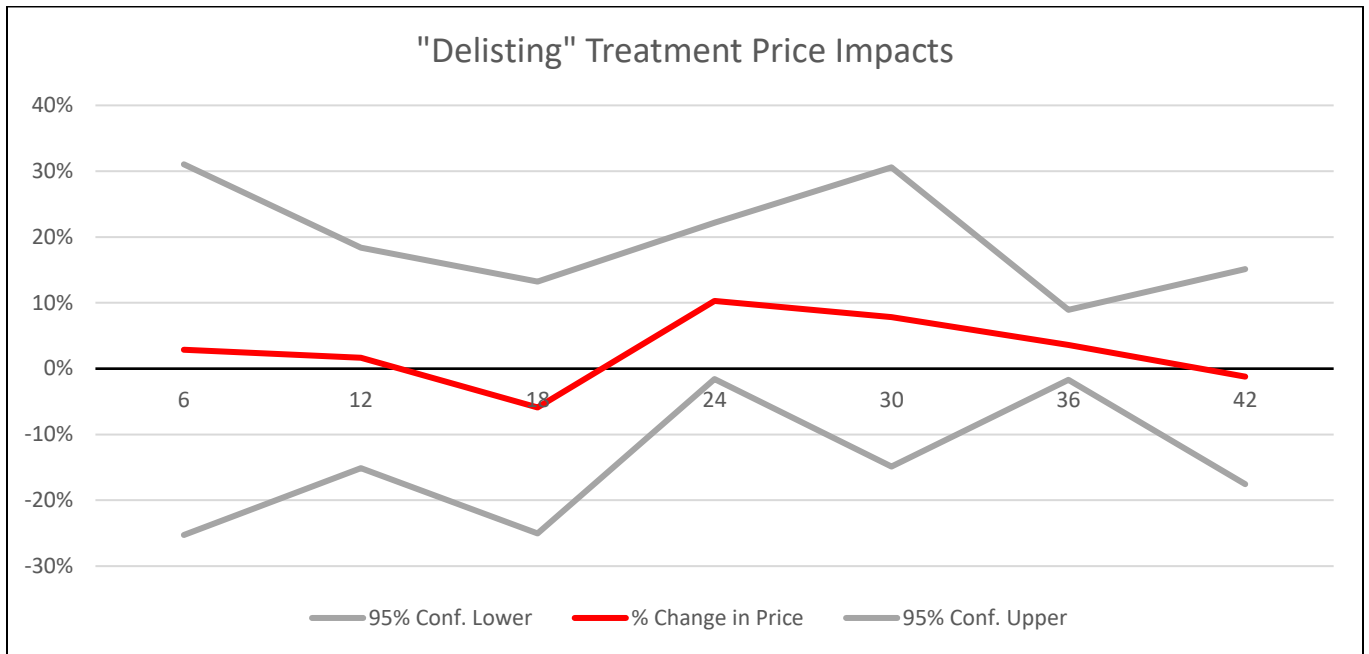


Figure 7 and Table 16 show that the “site delisting” treatment group was the only one in our study to report primarily positive sale price impacts. These positive impacts appear to be the most economically and statistically significant after a lag period of 24 months (2-years) at which point an average increase in home sale prices of 10.4% was observed. As Figure 7 displays, these positive impacts appear to be impermanent, having faded almost entirely by the lag period of 42 months (3.5 years) after the initial delisting date. Here it must be noted that the statistical significance of these “delisting treatment” coefficients is somewhat lacking, with the exception of the 24-month lag period coefficient previously mentioned. This could potentially be attributed to the comparatively smaller sample of home sales which were used to run the “delisting treatment only” model specification. As Table 6 in the data collection section displays; our “home sales after delisting” treatment group contained only 368 observations compared to 779, 846, and 835 observations for our “site listing”, “cleanup start”, and “cleanup end” treatment groups, respectively. This smaller sample size is due to the fact that only 2 of the 6 schools in our

study area ever received an NPL site delisting. Sample size notwithstanding, these findings are still very significant to our study given that the “site delisting” treatment was the only one to result in primarily positive impacts on nearby home sale prices in Yakima, Washington.

Table 17 details the results of our “Model Form E” which contains all four of our treatment group variables together in one regression. Model Form E and its results have been included to verify that the results of our individual treatment models (Forms A-D) are consistent and robust across model specifications.

Table 17: Results for All Treatments Included Regression Model (Form E)

All Treatments Regression Results (Model Form E)	
VARIABLES	Coefficients
Sold 0-6 Months After Cleanup Start	-0.0977** (0.0259)
Sold 6-12 Months After Cleanup Start	-0.0163 (0.134)
Sold 12-18 Months After Cleanup Start	0.0659 (0.0382)
Sold 18-24 Months After Cleanup Start	-0.212 (0.130)
Sold 24-30 Months After Cleanup Start	-0.0771 (0.103)
Sold 30-36 Months After Cleanup Start	-0.108 (0.0729)
Sold 36-42 Months After Cleanup Start	0.0819 (0.101)
Sold 0-6 Months After Cleanup End	-0.0281 (0.106)
Sold 6-12 Months After Cleanup End	-0.0697 (0.0862)
Sold 12-18 Months After Cleanup End	0.0380 (0.112)
Sold 18-24 Months After Cleanup End	-0.0164 (0.0735)
Sold 24-30 Months After Cleanup End	-0.00881

TABLE 17 (CONTINUED)	
VARIABLES	Coefficients
	(0.0726)
Sold 30-36 Months After Cleanup End	-0.111
	(0.0644)
Sold 36-42 Months After Cleanup End	-0.118***
	(0.0281)
Sold 0-6 Months After NPL Delisting	0.0289
	(0.110)
Sold 6-12 Months After NPL Delisting	0.0165
	(0.0652)
Sold 12-18 Months After NPL Delisting	-0.0589
	(0.0744)
Sold 18-24 Months After NPL Delisting	0.103*
	(0.0462)
Sold 24-30 Months After NPL Delisting	0.0785
	(0.0884)
Sold 30-36 Months After NPL Delisting	0.0362
	(0.0207)
Sold 36-42 Months After NPL Delisting	-0.0121
	(0.0636)
Sold 0-6 Months After NPL Listing	-0.0151
	(0.0774)
Sold 6-12 Months After NPL Listing	-0.00688
	(0.0223)
Sold 12-18 Months After NPL Listing	-0.115
	(0.0701)
Sold 18-24 Months After NPL Listing	0.00934
	(0.0522)
Sold 24-30 Months After NPL Listing	-0.0218
	(0.0572)
Sold 30-36 Months After NPL Listing	-0.0753
	(0.0585)
Sold 36-42 Months After NPL Listing	-0.0154
	(0.0319)
Constant	10.57***
	(0.0789)
Observations	18,757
R-squared	0.404
House Characteristics	YES
Census Block Group FE	YES
Month-by-Year FE	YES

Robust standard errors in parentheses

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

The inclusion of all four treatment groups together in one model specification does not appear to have significantly altered the signs or magnitudes of our regression coefficients. While some of the coefficients in Model Form E do display lesser statistical significance than their individual treatment model counterparts; this is to be expected when estimating a model form with so many treatment groups competing for significance.

6.2 Cost-Benefit Analysis Results

The results of our cost-benefit analysis can be found in Table 18.

Table 18: Cost Benefit Analysis Calculation and Net Benefit

Cost-Benefit Analysis Calculation	
Health Benefits	\$ 20,053,465.72
Tax Benefits	\$ 5,830.90
Property Sale Revenue Benefits	\$ 481,137.41
Total Benefits	\$ 20,540,434.03
(Total Costs)	\$ (1,275,971.60)
Net Benefit	\$ 19,264,462.43

As Table 18 shows, the remediations have resulted in an overwhelming net benefit for the city of Yakima, Washington and its residents. The tax and property sale revenue benefits alone total approximately 36% of the total remediation costs. When the substantial health benefits associated with avoiding lead-arsenate exposure are incorporated into these calculations, the result is a total benefit of \$19,264,462.43. Based on these calculations, the Yakima elementary school remediations appear to have resulted in significant net benefits. It bears re-stating here that the tax and property sale benefits listed above were only accrued at the 2 school sites in our study area which received a “delisting treatment” (as described in the Methods section). Had the other four sites received more thorough remediations which would have led to the same delisting treatment and “NFA” designation, it is possible that the net benefits could have been even

higher. This will be explored further in the Discussion section. Regardless of the delisting treatment only being applied to 2 of the 6 schools in our study area, it appears that the elementary school remediations have been an economically efficient policy response to the areawide lead-arsenate contamination found in Yakima, Washington.

CHAPTER VII

DISCUSSION

7.1 Discussion of Findings

The findings observed in this study are quite significant and can help us to build a better understanding of the public response to the presence of contaminated sites near residential areas. Based on our findings, the remediation of contaminated school sites is an extremely economically efficient policy response to legacy lead-arsenate pollution. Our models revealed that the presence of contaminated schools appears to depress nearby residential property values by up to 18.8% after the contamination is made known to the public (see Table 13). These depressed prices seem to have fully rebounded following the completion of cleanup activities and an ensuing NPL site de-listing. Our models estimated a 10.4% price increase persistent for up to 2 years following the de-listing date for homes selling within the attendance boundaries of remediated and de-listed schools (see Table 16). Perhaps most interestingly; our models estimated persistent and significant negative price impacts for homes selling within the attendance boundaries of schools which were remediated but never de-listed (see Table 15).

When viewed together, these findings begin to tell a bigger story regarding the public response to the discovery of contaminated sites and their ensuing remediations. The discovery of contaminated sites appears to lead to decreased nearby property values as consumers (homebuyers) become aware of the hazard and begin to capitalize said hazard into their purchasing decisions. Following the completion of thorough remediation efforts which ended in a site's de-listing from the NPL contaminated site register; there was a significant price increase for properties selling near the de-listed school sites. If, however, the remediation was completed but resulted in a designation of "Performance Monitoring Required" with no de-listing; no such

price increase was observed. Rather, our models estimated that property sale prices remained depressed within the attendance boundaries of these schools which were remediated but not de-listed. This suggests that Yakima homebuyers trust that the lead-arsenate hazard has been adequately addressed when remediations end in a site de-listing, but do not trust the efficacy of remediations which do not result in a de-listing. The significant price increases observed following site de-listings also demonstrate that the public of Yakima, Washington are willing to pay a premium to avoid exposure to environmental contaminants like lead-arsenate.

Our study was not, however, free from drawbacks or potential concerns. One concern regarding our findings stems from the relatively lower sample size of home sales used to model the impacts of site de-listing on property values. While our results were still economically and statistically significant for the de-listing treatment, a larger sample size would have provided more certainty regarding the significance of these results.

Another concern which bears mentioning here deals with our benefit-transfer of the Pichery et al. (2011) study's findings. It was this study which determined that children exposed to lead levels consistent with those observed prior to remediation at contaminated school sites in Yakima would incur lifetime healthcare costs \$3,304.79 in excess of the average costs incurred by children who avoided lead exposure. If this estimate of \$3,304.79 was inaccurate or not applicable to our study area, it could have negatively impacted our study's cost-benefit analysis. However, given that the lead concentrations and exposure frequencies studied in the work of Pichery et al. were extremely similar to those observed in our study area, we determined that the estimates of Pichery et al. (2011) would be the most applicable for use in our benefit transfer. Additionally, as Table 18 in the Results section displays, the health benefits totaled in excess of \$20 million. As such, the true lifetime savings for children who avoided lead exposure in our

study area could have been much lower while still yielding a significant net benefit resulting from the remediations. For example, healthcare savings of \$330.4 per child (one tenth of those estimated by Pichery et al. (2011)) would still yield a sizeable net benefit equal to \$1,215,863.91.

Our final area of concern surrounds the estimation of cost figures for the Gilbert Elementary remediations. In the absence of available data (due to statewide lockdowns caused by the COVID-19 pandemic), we estimated the total cost for the Gilbert Elementary remediation based on an average of the remediation costs observed elsewhere in our study area. There is no way for us to know how accurate this estimation was, however, considering that our cost benefit analysis yielded total net benefits in excess of \$19 million (see Table 18), we do not have reason to believe that our findings would change significantly based on the value of this one estimated cost figure equal to \$212,661.93.

7.2 Discussion of Policy Recommendations

Our study's results have a few strong policy implications which we will discuss here. We have observed that remediations which end in site de-listings lead to increased nearby property values while values have remained depressed near school sites which were remediated but not de-listed. Since only 2 school sites were de-listed in Yakima, a significant amount of net benefit has been lost out on. For the sake of exploring a hypothetical, we have applied the most significant home sale price impact observed from de-listing (a 10.4% increase persistent up to 2 years after de-listing) to the homes sold for 2 years following the remediations in school attendance boundaries which were remediated but not de-listed. Assuming that this 10.4% price increase were to stay consistent for all school sites; our hypothetical calculations here estimate the additional benefits which may have been accrued in the city of Yakima if all 6 school sites had been de-listed. These calculations and totals can be found in Table 19.

Table 19: Hypothetical Tax and Home Seller Benefits (Assuming all schools de-listed and consistent 10.4% price increase for de-listing)

Cost-Benefit Analysis: Hypothetic Tax Benefit Calculations (All Schools Delisted)					
True Sales	Hypothetical Sales	(Difference)	True Tax	Hypothetical Tax	(Difference)
\$ 16,220,382.15	\$ 17,426,164.49	\$ 1,205,782.34	\$ 196,574.81	\$ 211,187.69	\$ 14,612.88
Sum Total of Hypothetical Tax and Home Seller Revenue Benefits:					\$ 1,220,395.21

As Table 19 shows, the hypothetical tax and property sale revenue benefits total \$1,220,395.21. This represents an increase of \$733,426.90 (150.61%) over the actual property tax and property sale revenue benefits calculated in Table 9. While these figures are purely hypothetical, they do suggest that significantly greater net benefits could have been accrued in Yakima due to the remediations if all 6 had resulted in a site de-listing and similar price impacts to the actual de-listings which were observed and modelled in our study.

Our findings suggest that while the remediations resulted in extremely high net benefits for the city of Yakima (see Table 18); these benefits could have been even greater if more than 2 of the remediations had triggered an increase in nearby property values. Based on our observations and results, we have arrived at two policy suggestions which may aid in realizing these greater benefits. These suggestions are to prioritize achieving site outcomes of de-listing and designations of “NFA” in future contaminated site remediations, and/or to prioritize outreach and public awareness campaigns aimed at changing the public’s perceptions surrounding sites which have been successfully remediated but not de-listed from the NPL’s register of contaminated sites.

The benefits of prioritizing site de-listings are fairly straightforward. Our findings

suggested that these de-listings are the only signal which triggered a positive price response for properties near the remediated site. Assuming that the price impacts observed in our models remain consistent across the study area; achieving more site de-listing outcomes would likely to lead to greater total benefits as Table 19 suggests. This recommendation in particular is directed towards the school administrators in charge of the schools which received remediations but no de-listings, as the de-listing designations occur as a result of administrative actions taken by school officials to record environmental covenants at the remediated school sites. This de-listing designation has no bearing on the actual safety or cleanliness of the remediated sites and is, again, a purely administrative decision. According to EPA regulations, achieving a de-listing designation requires that “the EPA regional administrator approves a ‘close out report’ that establishes that all appropriate response actions have been taken or that no action is required” (EPA 2020). In the case of the remediated Yakima elementary schools, the “appropriate response actions” include recording environmental covenants at the remediated sites which ensure that future site uses will not risk disturbing the contaminated soil which has been “capped” or safely covered by layers of clean topsoil (ECY 2003). Based on our findings regarding the benefits of site de-listings, we would strongly recommend that school administrators at the sites which have not been de-listed begin working with the EPA to record these environmental covenants and push for de-listing designations.

The potential benefits associated with a public awareness and outreach campaign aimed at changing perceptions surrounding remediation outcomes could also be very significant. As the literature reviewed for this study has demonstrated; the impact of contaminated site discovery and remediation on nearby real estate values tends to depend less on the actual severity of the hazard and more upon how the public perceives said hazard (Slovic 2000; McCluskey and

Rausser 2001; Martin 2017). Regardless of whether a remediated school site receives a de-listing and “NFA” designation or no de-listing and a “Performance Monitoring Required” designation; the site in question has still been remediated to the point where the lead-arsenate hazard no longer poses a risk to children attending that school site. The only substantial difference in outcomes between a de-listed site and one which remains on the NPL register is that the site which remains on the NPL register must undergo periodic soil testing to ensure that the cleanups were successful and that no new contaminated material has found its way to the soil surface (ECY 2012). This fact does not appear to be reflected in the public response to the cleanups, as only the de-listed sites triggered positive price impacts. A public outreach campaign aimed at changing the public’s perceptions of the sites which were remediated but not de-listed could trigger positive price impacts at the aforementioned sites which remain on the NPL register. This could generate significant property tax and home sale revenue benefits for the city of Yakima, Washington.

In either case, additional funding would need to be secured under Washington State’s Model Toxics Control Act (MTCA) in order to achieve either more site de-listing outcomes or a shift in public perceptions regarding sites which were not de-listed. This brings us to our final policy recommendation: finding more efficient and dependable funding sources for the MTCA. As it stands, funding for the MTCA in Washington State is largely dependent on Hazardous Substance Tax revenues from the sale of petroleum products and pesticides in the state (RCW 82.21.030). Due to the extreme volatility of oil markets, the MTCA’s funding has been unreliable at best. This unreliable funding has been a major obstacle standing in the way of remediation activities at sites contaminated by legacy pesticide use in Washington State. One potential remedy to this issue could involve the state petitioning the federal government for

additional funding to remediate the state's remaining contaminated sites. Given that lead-arsenate pesticides were applied to orchards in Washington State at the recommendation of the United States Department of Agriculture (USDA); it stands to reason that the USDA should contribute to remediating the lasting damage caused by these pesticides (Schick and Flatt 2015; Martin 2017).

7.3 Discussion of Future Research

Within Washington State, studies investigating the public response to lead-arsenate pesticide remediations have now been conducted in both Chelan and Yakima counties. While these two counties have the most extensive histories of lead-arsenate pesticide use; historic lead-arsenate pesticide use has also necessitated remediations elsewhere in the state. In north central Washington's Okanogan County, for example, the discovery of unsafe lead and arsenic levels necessitated the remediation of school facilities in the Brewster and Omak school districts (ECY 2003). Our understanding of the public response to school site remediation could greatly benefit from future studies which evaluate the impacts of these Okanogan County cleanups.

Though our study focused only on evaluating the impact of elementary school remediations on nearby housing values, the remediations in Yakima, Washington were not strictly limited to school sites. In addition to the 6 elementary schools which were remediated; 2 of Yakima's city parks also received remediation between 2002 and 2003 due to the discovery of unsafe lead and arsenic levels in the soil. Future studies examining the impact that these park cleanups had on nearby property values could greatly expand our understanding of the public's perception of contaminated soil. By undertaking research into site remediation impacts in new study areas and studying remediation impacts depending on site usage (i.e. park remediations vs. elementary school remediations), future studies may continue contributing to our understanding

of the public's responses to remediation. It is this understanding which can help facilitate the implementation of more efficient policy responses intended to address areawide lead-arsenate soil contamination in Washington State.

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APPENDICES

Appendix A: Variable Definitions

Name in Stata	Definition
<i>Sales Variables</i>	
lnrealsalepr	dependent variable - log of home sale price adjusted for inflation to \$ 2012
saledate	date on which each home was sold
Sale_month	month in which each home was sold
Sale_year	year in which each home was sold
<i>Housing Variables</i>	
age	age of each home sold
age2	quadratic term for age
totalarea	total square footage of each home sold
numbeds	number of bedrooms associated with each sold home
Acres	number of acres of land associated with each sold home
quality	relative building quality of each home sold
bldg_style	construction style of each home sold
<i>Neighborhood Variables</i>	
GEOID10	U.S. Census block ID
BLKGRPCE10	U.S. Census block group number
<i>Elementary School Cleanup Treatment Variables</i>	
Site_list_date	NPL listing date
Site_cleanup_start	date cleanups were started at each contaminated school site
Site_Cleanup_end	date cleanups were completed at each contaminated school site
Site_delist_date	Date of NPL delisting for remediated sites
Cleanup_Duration	length of each site remediation (measured in days)
days_from_list_to_sale	days from nearby site NPL listing date to home sale date
0-6_mo_after_list	homes selling 0-6 months after NPL listing of a nearby school site
6-12_mo_after_list	homes selling 6-12 months after NPL listing of a nearby school site
12-18_mo_after_list	homes selling 12-18 months after NPL listing of a nearby school site
18-24_mo_after_list	homes selling 18-24 months after NPL listing of a nearby school site
24-30_mo_after_list	homes selling 24-30 months after NPL listing of a nearby school site
30-36_mo_after_list	homes selling 30-36 months after NPL listing of a nearby school site
36-42_mo_after_list	homes selling 36-42 months after NPL listing of a nearby school site
days_from_cleanup_start	days from the start of cleanup activities at a nearby school to home sale date
0-6_mo_after_start	homes selling 0-6 months after the start of cleanups at a nearby school site
6-12_mo_after_start	homes selling 6-12 months after the start of cleanups at a nearby school site
12-18_mo_after_start	homes selling 12-18 months after the start of cleanups at a nearby school site
18-24_mo_after_start	homes selling 18-24 months after the start of cleanups at a nearby school site
24-30_mo_after_start	homes selling 24-30 months after the start of cleanups at a nearby school site
30-36_mo_after_start	homes selling 30-36 months after the start of cleanups at a nearby school site
36-42_mo_after_start	homes selling 36-42 months after the start of cleanups at a nearby school site
days_from_cleanup_end	days from the end of cleanup activities at a nearby school to home sale date

Name in Stata	Definition
0-6_mo_after_end	homes selling 0-6 months after the end of cleanups at a nearby school site
6-12_mo_after_end	homes selling 6-12 months after the end of cleanups at a nearby school site
12-18_mo_after_end	homes selling 12-18 months after the end of cleanups at a nearby school site
18-24_mo_after_end	homes selling 18-24 months after the end of cleanups at a nearby school site
24-30_mo_after_end	homes selling 24-30 months after the end of cleanups at a nearby school site
30-36_mo_after_end	homes selling 30-36 months after the end of cleanups at a nearby school site
36-42_mo_after_end	homes selling 36-42 months after the end of cleanups at a nearby school site
days_from_Delist_to_sale	days from nearby site NPL de-listing date to home sale date
0-6_mo_after_delist	homes selling 0-6 months after NPL de-listing of a nearby school site
6-12_mo_after_delist	homes selling 6-12 months after NPL de-listing of a nearby school site
12-18_mo_after_delist	homes selling 12-18 months after NPL de-listing of a nearby school site
18-24_mo_after_delist	homes selling 18-24 months after NPL de-listing of a nearby school site
24-30_mo_after_delist	homes selling 24-30 months after NPL de-listing of a nearby school site
30-36_mo_after_delist	homes selling 30-36 months after NPL de-listing of a nearby school site
36-42_mo_after_delist	homes selling 36-42 months after NPL de-listing of a nearby school site

Appendix B: Regression Analysis Code (Stata)

*** CODE FOR ALL TREATMENTS TOGETHER

```
xi: reg lnrealsalepr y06_mo_after_start134 y612_mo_after_start y1218_mo_after_start  
y1824_mo_after_start y2430_mo_after_start y3036_mo_after_start y3642_mo_after_start  
y06_mo_after_end141 y612_mo_after_end y1218_mo_after_end y1824_mo_after_end  
y2430_mo_after_end y3036_mo_after_end y3642_mo_after_end y06_mo_after_delist166  
y612_mo_after_delist y1218_mo_after_delist y1824_mo_after_delist y2430_mo_after_delist  
y3036_mo_after_delist y3642_mo_after_delist y06_mo_after_list173 y612_mo_after_list  
y1218_mo_after_list y1824_mo_after_list y2430_mo_after_list y3036_mo_after_list  
y3642_mo_after_list totalarea numbeds age age2 acres quality_exc_vg i.bldg_style i.blkgrpce10  
i.sale_year*i.sale_month if realsalepr>0 & realsalepr<305208 & totalarea>0 & totalarea<2896 &  
numbeds>0 & numbeds<5 & age<162 & acres>0.1 & acres<.41, cluster(blkgrpce10)  
outreg2 using All_Treat_Reg_Results.doc, replace ctitle(All Treatments Model) label  
keep(y06_mo_after_start134 y612_mo_after_start y1218_mo_after_start y1824_mo_after_start  
y2430_mo_after_start y3036_mo_after_start y3642_mo_after_start y06_mo_after_end141  
y612_mo_after_end y1218_mo_after_end y1824_mo_after_end y2430_mo_after_end  
y3036_mo_after_end y3642_mo_after_end y06_mo_after_delist166 y612_mo_after_delist  
y1218_mo_after_delist y1824_mo_after_delist y2430_mo_after_delist y3036_mo_after_delist  
y3642_mo_after_delist y06_mo_after_list173 y612_mo_after_list y1218_mo_after_list  
y1824_mo_after_list y2430_mo_after_list y3036_mo_after_list y3642_mo_after_list) addtext(House  
Characteristics, YES, Census Block Group FE, YES, Month-by-Year FE, YES)
```

*** CODE FOR START TREAT ONLY

```
xi: reg lnrealsalepr y06_mo_after_start134 y612_mo_after_start y1218_mo_after_start  
y1824_mo_after_start y2430_mo_after_start y3036_mo_after_start y3642_mo_after_start totalarea  
numbeds age age2 acres quality_exc_vg i.bldg_style i.blkgrpce10 i.sale_year*i.sale_month if  
realsalepr>0 & realsalepr<305208 & totalarea>0 & totalarea<2896 & numbeds>0 & numbeds<5 &  
age<162 & acres>0.1 & acres<.41, cluster(blkgrpce10)  
outreg2 using Start_Treat_Reg_Results.doc, replace ctitle(Start Treatment Only Model) label  
keep(y06_mo_after_start134 y612_mo_after_start y1218_mo_after_start y1824_mo_after_start  
y2430_mo_after_start y3036_mo_after_start y3642_mo_after_start) addtext(House Characteristics,  
YES, Census Block Group FE, YES, Month-by-Year FE, YES)
```

*** CODE FOR END TREAT ONLY

```
xi: reg lnrealsalepr y06_mo_after_end141 y612_mo_after_end y1218_mo_after_end  
y1824_mo_after_end y2430_mo_after_end y3036_mo_after_end y3642_mo_after_end totalarea  
numbeds age age2 acres quality_exc_vg i.bldg_style i.blkgrpce10 i.sale_year*i.sale_month if  
realsalepr>0 & realsalepr<305208 & totalarea>0 & totalarea<2896 & numbeds>0 & numbeds<5 &  
age<162 & acres>0.1 & acres<.41, cluster(blkgrpce10)  
outreg2 using End_Treat_Reg_Results.doc, replace ctitle(End Treatment Only Model) label  
keep(y06_mo_after_end141 y612_mo_after_end y1218_mo_after_end y1824_mo_after_end  
y2430_mo_after_end y3036_mo_after_end y3642_mo_after_end) addtext(House Characteristics, YES,  
Census Block Group FE, YES, Month-by-Year FE, YES)
```

*** CODE FOR DELIST TREAT ONLY

```
xi: reg lnrealsalepr y06_mo_after_delist166 y612_mo_after_delist y1218_mo_after_delist
y1824_mo_after_delist y2430_mo_after_delist y3036_mo_after_delist y3642_mo_after_delist totalarea
numbeds age age2 acres quality_exc_vg i.bldg_style i.blkgrpce10 i.sale_year*i.sale_month if
realsalepr>0 & realsalepr<305208 & totalarea>0 & totalarea<2896 & numbeds>0 & numbeds<5 &
age<162 & acres>0.1 & acres<.41, cluster(blkgrpce10)
outreg2 using Delist_Treat_Reg_Results.doc, replace ctitle(De-Listing Treatment Only Model) label
keep(y06_mo_after_delist166 y612_mo_after_delist y1218_mo_after_delist y1824_mo_after_delist
y2430_mo_after_delist y3036_mo_after_delist y3642_mo_after_delist) addtext(House Characteristics,
YES, Census Block Group FE, YES, Month-by-Year FE, YES)
```

*** CODE FOR LIST TREAT ONLY

```
xi: reg lnrealsalepr y06_mo_after_list173 y612_mo_after_list y1218_mo_after_list y1824_mo_after_list
y2430_mo_after_list y3036_mo_after_list y3642_mo_after_list totalarea numbeds age age2 acres
quality_exc_vg i.bldg_style i.blkgrpce10 i.sale_year*i.sale_month if realsalepr>0 & realsalepr<305208 &
totalarea>0 & totalarea<2896 & numbeds>0 & numbeds<5 & age<162 & acres>0.1 & acres<.41,
cluster(blkgrpce10)
outreg2 using List_Treat_Reg_Results.doc, replace ctitle(Listing Treatment Only Model) label
keep(y06_mo_after_list173 y612_mo_after_list y1218_mo_after_list y1824_mo_after_list
y2430_mo_after_list y3036_mo_after_list y3642_mo_after_list) addtext(House Characteristics, YES,
Census Block Group FE, YES, Month-by-Year FE, YES)
```