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The Economic Impacts of Forest Pathogens in Washington State: A Hedonic Approach

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THE ECONOMIC IMPACTS OF FOREST PATHOGENS

IN WASHINGTON STATE: A HEDONIC APPROACH

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ABSTRACT

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An increase in the incidence of forest pathogens in the Western US has created new resource management issues. In this research I employ a dataset of 170,141 housing transactions in twelve Western Washington counties to quantify the impacts of parasitic forest damage on the proxy real estate market. Specifically, I estimate a set of hedonic fixed effects models to control for omitted variable bias and spatial autocorrelation. Results show statistically significant impacts on property values in the presence of species specific and aggregate defoliation, suggesting new information for forestry management and policy.

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CHAPTER 1
INTRODUCTION

Whether for recreation, aesthetics, or bequeathment, forests hold special value to societies around the world. For Western Washington, the value of this environmental amenity may be threatened as levels of forest insects and other defoliators reach epidemic levels. While normal populations of native pathogens are integral to the natural process of thinning weak, damaged stands and increase biodiversity in the forest environment (Winder and Shamoun, 2006), Washington State has experienced elevated levels of defoliation in the past few decades. According to the Washington Department of Natural Resources, levels of pathogen-related forest damage has doubled since the 1980's and encompasses some 1.08 million acres in 2012 (Dozic et al., 2015) (see Figure 1). Other studies agree that tree mortality in the Northwest has doubled every seventeen years since 1955, in part due to pathogenic activity (Van Mantgem et al., 2009).

Currently, national management plans, such as the *US Forest Service National Strategic Framework for Invasive Species Management* (USDA, 2013) and the *Western Bark Beetle Strategy* (U.S. Forest Service, 2011), identify threats and prioritize efforts; however, such strategies come at great cost. For example, in 2011, the Forest Service budgeted $101.5 million for Bark Beetle control alone, with similar levels of funding to be appropriated through 2016 (U.S. Forest Service, 2011; USDA, 2013). To maximize effectiveness and justify its efforts, the Forest Service is very clear that the best science should be considered to prioritize activities by, among other things, socio-economic impacts (USDA, 2013). Scientific research groups such as the Western Bark Beetle Research Group have also been formed by the USDA to study the entomological and other "application-motivated" work to help inform best management practices.

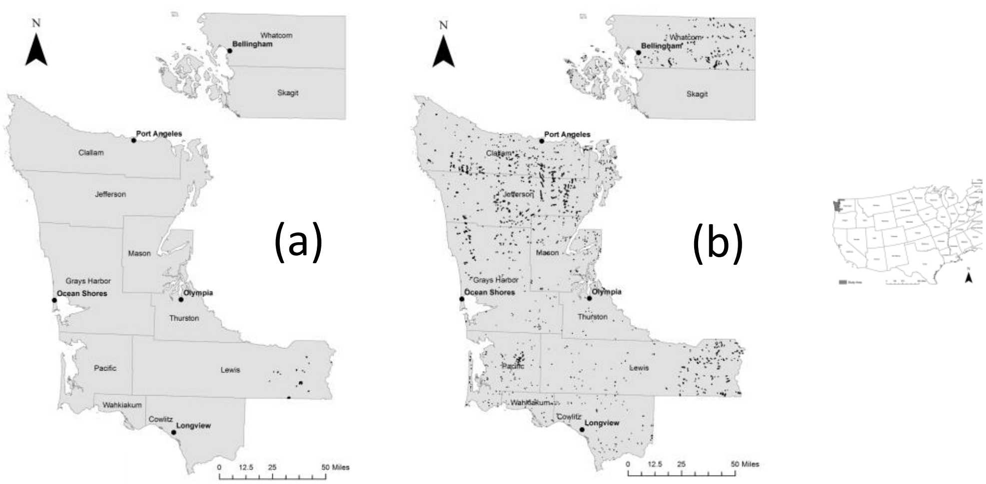

Figure 1: Blight in Western Washington: 1986 (a) and 2012 (b)

At a regional level, the Washington Invasive Species Council, formed in 2006, combines the efforts of multiple state and federal agencies. The council is charged with developing baselines, plans and recommendations focused on prevention and treatment of local infestations. In 2008, the Council developed a 20-year Strategic Plan to address the above mandate which, among others, suggests economic modeling to help inform prioritization (Washington Invasive Species Council, 2008).

While many environmental externalities, such as air and water pollution, spill over into the national or global arena, the effects of forest damage are relatively localized and thus easier to quantify and manage. However, the information needed to properly manage externalities is currently limited. While management can leverage market values, such as timber products and fire damage, (USDA, 2013; U.S. Forest Service, 2011), impacts to any non-market environmental services poses externalities beyond classical markets, especially where heavy wild land-urban interface (WUI) exist (Holmes et al., 2010). Therefore, as forest management strategies evolve, it is important to support them with complete market as well as non-market information.

In this paper, I help fill the gap of regional knowledge concerning the total economic impacts of forest blight in Washington State. Using the Washington State real estate market as a measure of consumer preference, I empirically estimate society's willingness to pay for blight mitigation measures. Generally, I find that small areas of forest blight may improve real estate value by, among other potential causes, opening up views. However, when high or epidemic areas of defoliation persist, negative economic impacts may stem from aesthetic decline and increased fire risk. Additionally, I confirm that the economic impacts can be derived from well beyond personal property.

Chapter 2 explores literature on forest values, the blight problem that they face and studies that have attempted to measure the economic impacts of blight. Chapter 3 discusses the data used in this study and the use of geographic information systems. Chapter 4 is a journal article which, aside from an independent introduction and literature review, contain sections on methods, empirical issues and a discussion. Chapter 5 concludes the paper with a discussion on policy, problems, and future work.

CHAPTER 2
LITERATURE

This study, ultimately concerned with estimating the economic effects of blight in forests, draws its motivation from a dense history of studies, methods and results; this chapter examines all these components of the literature. In the sections below I synthesize literature concerning nonmarket forest values, the problems facing forest, hedonic models and studies that specifically examine the economic impacts of forest blight using hedonic models and other methods. Finally, I identify gaps in the literature and discuss the improvements that this paper offers in terms of our understanding of non-market forest value.

2.1 Forest Values

The value of forest, for the purposes of this discussion, generally refer to value that is apart from what forest will explicitly fetch on the timber market. In other words, trees have worth beyond their use as a raw material. Some non-market forest benefits, discussed below, include carbon sequestration, recreational use, and general aesthetics (Pearce, 1997).

It is commonly known that trees offer carbon sequestration, which is of increasing importance in this era of climatic change. Among the 24 million acres considered roadless National Forest in the contiguous United States, their value as a carbon sequestration mechanism is estimated between $490 million and $1 billion dollars a year (Loomis and Gonza, 2000). Other studies mention that carbon sequestration by all United States forests may reach $3.4 billion dollars per annum (Kieger, 2001). Due to their relatively high densities, rainforest can offer some of the highest global benefits of carbon sequestration. Building upon global warming cost literature, Pearce (1997) estimates that rainforest can offset $600-$4400/ha in global warming damages depending on the density of the forest. Carbon sequestration can also be valued on a more granular scale. For example, Brack (2002) estimates that the value of carbon sequestration in Canberra, Australia from 2008-2012 ranges from $20-$67 million (US). While it is not directly estimated, Littell et al. (2010) suggest that climate change may affect the carbon sequestration capacities of Washington State, which contain temperate rain forest such as the Hoh Rain Forest in the Olympic peninsula.

Forest can greatly facilitate recreational and ecotourism opportunities, and as such, are a popular way to measure nonmarket values by observing visitation and fees they draw from the public. In Washington State it is estimated that the average person spends 56 days a year recreating outdoors (Briceno et al., 2015). Studies in this area are numerous, toping some two dozen in the United States alone since 1979 (Loomis, 2000). Loomis (2000) comprehensively evaluates these studies to derive an average willingness to pay of $42 a day for the use of select wilderness areas in the US. Loomis (2000) ultimately multiplies the aforementioned average with total recreation days in wilderness areas to settle on an estimated annual value of select wilderness recreation of $600 million. Studies focused on recreational values outside of the United States find similar values. Matsiori et al. (2012) estimate the total recreational value of the Pertouli University Forest in Greece is € 565,191,652 a year while forest recreation in Poland shows a willingness to pay € 0.64-6.93 per trip/person (Bartczak, 2008).

The value of general forest aesthetics has also been extensively studied in the literature. In this case, aesthetics refer to forest providing a view or some level of beautification of an area. Interestingly, some studies find particular forest types and arrangements to have negative impacts, especially if they obstruct views and encroach on useful or open land (Seong-Hoon, 2008), while many find positive impacts (*inter alia* Mansfield et al., 2005; Netusil, 2000 and Thompson et al., 1999). Walls et al. (2015), while estimating the impacts of various land cover views in St. Luis County, Missouri, find that a 10% increase in forest cover view leads to an estimated 0.6% increase in property values. Other studies, using similar hedonic methods, show that urban forested parcels hold value and living adjacent to private forest can offer statistically significant positive values (Mansfield, 2005).

Estimates provided by Cho et al. (2008) show that in more rural properties in Knoxville, Tennessee, living 100m closer to an evergreen forest patch is valued at $692 while a similar move toward deciduous trees reduced value by almost the same amount. However, urban core properties positively value deciduous and mixed cover. The mixed nature of aesthetic forest value is farther explained by Netusil et al. (2010). Using hedonic real estate models, Netusil et al. (2010) find that people living in sparsely forested parcels around Portland, Oregon value additional tree cover, while other, more densely forested regions of the city negativity valued additional trees. Further, examining socio-economic class and forest valuation, Thériault et al. (2002) finds that forest can negatively impact real estate up to -9% in poor neighborhoods while adding up to 15% to those living in more affluent areas.

2.2 Blighting Agents in Washington

While there are many stressors that threaten forests identified in the above literature (e.g. clearcutting), this paper focuses on the reduction of forest health as a result of forest blight. Forest blight, or defoliators, are defined in this research as insects, disease or fungi which can be exasperated by other exogenous conditions such as climate change and fire suppression (Bentz et al., 2010). Accordingly, the following section highlights literature that discusses blighting agents present in Washington State and the possible factors that have led to an increase in their numbers (Mantgem et al., 2009).

Forest damage in Washington State is not limited to any single species. The Douglas Fir Beetle (*Dendroctonus pseudotsugae Hopkins*), which attacks the Douglas fir (*Pseudotsuga menziesii*) is a thinning agent for already weak and damaged trees, but epidemic levels of the beetle can lead to attacks on otherwise healthy hosts (Schmitz and Gibson, 1996) . In Washington, the Douglas Fir Beetle has killed an estimated 27,000 acres in 2014 (Dozic et al., 2015). Similarly, the Pine Beetles (*Dendroctonus ponderosae Hopkins, Dendroctonus brevicomis LeConte & Ips spp*.) caused mortality in over 143,000 acres in 2014. Fir Engraver (*Scolytus ventralis*), considered a secondary pest that attacks already stressed trees, can thrive during existing outbreaks of other species or in drought ridden and overcrowded forest. In Washington State, 31,000 acres were estimated to be killed by the fir engraver in 2014 (Dozic et al., 2015). Characterized by their naturally peeling copper color bark, Pacific Madrone (*Arbutus menaies*) have been declining since the 1960's in the Pacific Northwest, especially in urban settings. While research concerning the causes of madrone decline is ongoing, several different canker and fungi have been found to cause damage including Nattrassia mangifera and Fusicoccum aesculi (Elliot et al., 2002). As many agents attack one type of tree, the Western Spruce Budworm (*Choristoneura occidentalis*) causes damage to the widest variety of tree stands ranging from 15 different firs and pines including the Douglas fir, Grand fir, Ponderosa pine, Limber pine, and ornamental trees like the Norway and Scotch pine (Fellin, 1992).

Not all damaging agents in Washington State fall under the insect category. White Pine Blister Rust (*Cronartium ribicola*) spores attach to the white pine (*Pinus strobus*) needles, eventually causing cankers and tree stand death (Dekker-Robertson et al. 2015). Dekker-Robertson (2013) estimated that 5 million cubic feet of white pines are lost in the Pacific Northwest annually due to the disease. Various root diseases including Annosum root disease (*Heterobasidion annosum*), Brown cubical butt rot (*Polyporus schweinitzii*), Tomentosus (*Inonotus tomentosus*), Laminated root rot (*Phellinus weirii*), and Armillaria root disease (*Armillaria mellea*) all significantly contribute to stand mortality in almost all tree varieties, particularly the Douglas fir and mountain hemlock (Hessburg et al., 1994).

Forest disturbances in Washington State can be attributed to several factors. Decades of silvicultural practices and fire suppression have contributed to a substantially overstocked forest (Hessburg et al., 1994). Dense forests, containing greater species uniformity, provide a catalyst for rapid growth and defoliator spread (Bentz et al., 2010). Crowded conditions can also invite various root diseases which weaken stands that are otherwise resilient to attack (Hessburg et al., 1994). Accompanying density, climate change may also exacerbate levels of blighting agents in northwestern US forests. Although a full discussion of climate change in the Pacific Northwest is beyond the scope of this work, entomological research suggests that forest insects, particularly bark beetle, respond positively to warming trends (Bentz et al., 2010). According to Bentz and others (2010), some defoliator species take several years to produce a single generation depending on the climate; however, as temperatures increase, the probability of defoliators reproducing in one year also increases. Normal defoliator mortality rates also decrease due to warm temperatures (Régnière and Bentz, 2007). Thus, in the face of increased forest density and climatic change, volatility in even native species loads has become an increasingly important topic in forest management

2.3 History of Blight Specific Research

This section highlights several studies that specifically investigates the economic impacts of forest blight. First, I discuss papers that use stated preference and travel cost methods. While the results of these studies are not derived in the same fashion as in my research, they are attempting to elicit the same type of information about the cost of blighted forest. Secondly I briefly explain the hedonic method and delve into existing literature that employ the hedonic method to estimate the impacts of forest blight.

2.3.1 CVM and Travel Cost Methods

With the exception of Payne et al. (1973), who use early hedonic methods, most older studies employ survey based contingent valuation (CVM) or travel cost methods to measure forest health and public welfare. CVM builds off of neoclassical theory where consumers maximize their utility over a basket of goods given a budget constraint. When a respondent indicates that they are willing to pay for an amenity, their response describes how much they are willing to give up in terms of dollars to remain at the same level of utility as before (Kramer et al., 2003). Travel cost methods use the distance and frequency people travel to a site as a measure of value. The amount spent to reach a site can ultimately be tracked over time at one location, or, compared against other similar places in the face of some environmental change (Parsons, 2003).

By using travel cost methods to compare campground attendance between blighted and healthy park attendance in the Targhee National Park, Michalson (1975) finds consumer surplus losses of $510,362 in blighted areas.[1] Similarly, Leusher and Young (1978) find losses of $1,332,400 in east Texas campsites when compared to their healthier counterparts. Between 1981 and 1990, Walsh and others (see Walsh and Olienyk 1981, Walsh et al., 1981; Walsh et al.,1990 and Loomis and Walsh, 1988) published a series of novel papers focused on the economic impacts of pine beetle and spruce budworm damage in the Colorado Rocky Mountains. Using travel cost and contingent valuation methods, they find that, for a 15 percent decrease in forest health, recreational consumer surplus drops $11.60 per person (1981), and negative real estate impacts range from $896-$907. Finally, Walsh and others (1990) find that the average annual willingness to pay for forest protection is $52 per household.

Numerous survey studies yield a wide-range of willingness to pay figures, often varying due to program nature and geographic region. Asking households their willingness-to-pay for blight control, Jakus and Smith (1991) find that households would pay $348-$474 in the north-central Maryland and south-central Pennsylvania areas depending on whether it was facilitated by a private or public program. Haefele et al. (1992) find a willingness to pay of $103 for increased forest quality in the Southern Appalachian Mountains. Miller and Lindsay (1993) find a willingness to pay for gypsy moth control programs in New Hampshire of $43 to $70. Holmes and Kramer (1996) use CVM to elicit an annual willingness to pay of $11-$36 per person to help protect the

[1] Dollar amounts cited in this paper are reported as they appear in the original articles and are not adjusted to current dollars. For reference, the multipliers, as calculated from the CPI for converting 1970 dollars to 2015 dollars are 6.10, 2.87, 1.81, 1.37 for 1970, 1980, 1990, and 2000 respectively.

health of forest in and near the Great Smoky Mountains National Park. Finally, using contingent survey methods, Kramer et al. (2003) estimates a willingness to pay of $28 per person to reduce forest damage in the Appalachian Mountains.

2.3.2 Hedonic Methods

Described in the seminal work of Rosen (1974), hedonic real estate models attempt to quantify the aforementioned non-market values by observing the willingness to pay for a home given its structural and environmental qualities. Generally, single family parcels cannot be used for logging or commercial purposes; therefore, the value of forest health derived from the hedonic function is connected to buyers' personal preferences, influenced by aesthetic consideration, recreational use, privacy, blocking eyesores, etc., and is separate from profitmaking associated with lumber harvest. In this way, society "reveals" its non-market valuation of forests when a home is purchased.[2]

Using hedonic models, Thompson et al. (1999) attempt to quantify the impact of insect damage on a small neighborhood in the Lake Tahoe Basin. Situated in a vacation destination, this area features expensive real estate, with the average home valued at $334,000, and is surrounded by forest which had been heavily damaged by infestation. The results show that the presence of forest blight decreases the value of a median-priced Tahoe home by $26,390. However, the coefficients derived by Thompson et al. (1990) in a distinct socio-economically area may overstate damages in Washington

[2] See methods and empirical issues section of this paper for a more complete discussion of the hedonic method.

State. Price et al. (2010) focuses on the mountain pine beetle's (MPB) non-market impacts and the willingness to pay for mitigation using a hedonic real estate model in Grant County Colorado from 1996-2006. The study includes usual structural and area variables such as rooms, square feet, acres etc., as well as a treatment group, in this case, forest blight at different distances. To control for nearby unaccounted-for homes affecting the price on one another (spatial autocorrelation), the authors use spatially-weighted terms assigned by nearest neighbor. Results show that there are significant negative effects of blight ranging from -0.1%, -0.008%, and -0.003% per number of trees killed for 0.1, 0.5, and 1km distances, respectively. Accordingly, the paper finds the implicit price of a dead tree to be $648, $43 and $17. Although not conducted in Washington State, Price et al.'s (2010) results give general insight into the functional relationship that exists between property value and forest blight while, like this work, advances the applied use of geographic information systems (GIS).

Other literature using hedonic models finds mixed or even positive impacts of forest defoliation. Holmes et al. (2006) estimate the effect of hemlock woolly adelgid infected hemlocks on housing values in Sparta, New Jersey. This study is particularly useful in that damaged trees are classified into different thresholds as well as into different distances ranging from the parcel level to 1km beyond the parcel, allowing for comparison of different damage thresholds and tests whether impacts extend beyond parcels alone. The authors find evidence that moderate tree health negatively impacts residential value while severe damage was statistically insignificant and that fully dead hemlock yield positive impacts on real estate prices. As a justification for positive impacts, the authors cite possibilities such as additional light entering the forest and favorable new growth. This study lends important contributions to my work and the literature as a whole by showing that property value may be contingent on different levels of blight severity, and, like Price et al. (2010), effects can be induced from beyond an individual parcel.

In a similar fashion to Holmes et al. (2006), Holmes et al. (2010) use both spatial and fixed effects hedonic models to estimate the impacts of woolly adelgid infected hemlock on house prices in West Milford, New Jersey. The authors employ remote sensing data to delineate woolly adelgid outbreak into several damage categories ranging from healthy to dead, finding that, in general, outbreaks have significant negative impacts on real estate. Properties subjected to hemlock decline or damage experienced losses in value ranging from 1 to 1.6%.

Using several different spatial hedonic models, Hansen and Naughton (2013) estimate that spruce bark beetle outbreaks in south-central Alaska can increase assessed property values by 2.1% and 3.7% when damage occurs within 0.1 - 0.5km or 0.5 - 1.0km from a home. Not unlike Washington State, properties in this region are close to dramatic ocean and mountain views. The authors suggest that the thinning effects of disturbance release pending views and may outweigh any negative effects inherent to the disturbance itself.

The US Forest Service and various interest groups stress proactively managing forest blight (U.S. Forest Service, 2011; USDA, 2013). In attempts to empirically show the impacts of proactive management, Kovacs et al. (2011) predicts the spread of sudden oak death (SOD) in California from 2010-2020, and estimates the total removal costs and property loss at 2020 levels. Primary results claim that, if forecast assumptions hold true, 10% of 734,000 oak trees on developed land will need to be treated or removed by 2020 at a cost of $7.5 million, and property will be reduced by up to $135 million. Hypothetically, if all 734,000 trees needed treatment or replacement it would cost $729 million and the loss of real estate value would top $8.3 billion.

2.4 Literature Gap

Literature addressing the relationship between forest blight and housing values has produced mixed results. For example, communities in Lake Tahoe (Thompson et al., 1999) value forest differently than in southcentral Alaska (Hansen and Naughton, 2013) and all societies conceptually value forest health differently from year to year depending on economic health and changing social norms. Previous works have searched for impacts on parcels or proximities extending out to 1km in a relatively focused study area. Accordingly, literature emphasizes the need for larger geographical study areas and to expand the search for externalities as they exist beyond the parcel to facilitate more relevant regional policy (Rosenberger et al., 2012).

This paper builds on existing literature in several ways (See Table 1). I investigate the impacts of forest blight across a sizable regional arena by employing, to my knowledge, the largest dataset seen in blight research, comprising of 172,119 western Washington housing transactions spanning 26 years. I extend the search for externalities beyond the parcel to a 5km radius and estimate census block and repeat sales fixed effects models to avoid various forms of bias inherent in other hedonic models (see methods and empirical issues section). To estimate aggregate, as well as select individual blight impacts, I leverage an expansive study area which harbor several different blighting agents. To offer an explanation of inconsistent results in recent literature, I suggest a non-linear relationship between forest blight and real estate values.

Table 1 Hedonic Studies of Forest Blight

Year	Study	Geographical Area	Number of Observations	Impacts
1973	Payne et al.	N/A	N/A	N/A
1999	Thompson et al.	84,240 ha	100	Negative
2006	Holmes et al.	39 sq. mi.	3379	Negative
2010	Holmes et al.	80 sq. mi.	4,373	Mixed
2010	Price et al.	4842 sq. km	3681	Negative
2013	Hansen and Naughton	N/A	8796	Positive
2015	Blair et al.	19,097 sq. mi	170,141	Mixed

In the next chapter on data and data analysis, I discuss where and how information was gathered for this research. Further, I identify each variable's level of validity and potential error. Finally, I explore the role of Geographical Information Systems (GIS) in natural resource economics and lay out detailed steps on how it is used in this analysis.

CHAPTER 3
DATA, ANALYSIS AND THE USE OF GEOGRAPHIC INFORMATION SYSTEMS

Geographic information systems or "GIS" has transformed the depth and scope of what is possible in environmental economics. By analyzing physical, environmental and political data across space, GIS can add precision to otherwise estimated metrics or new solutions altogether when combined with economic and econometric modeling. By allowing research to move away from strong spatial assumptions and antiquated means of data collection, economist can now precisely measure and query treatment variables, such as proximity and size of environmental amenities (Bateman et al., 2002). Additionally, GIS can aid in addressing classical methodological issues such as spatial autocorrelation and omitted variables (Parmeter and Pope, 2012).

The term GIS can take on different forms and scales. It may refer to a single piece of software or a series of models and frameworks build across many platforms. In this chapter, I accept the definition of GIS as "An integrated collection of computer software and data used to view and manage information about geographic places, analyze spatial relationships, and model spatial processes." (ESRI, 2015). In this way, GIS as a field is an overarching term not limited to a single program or operational function.

Within this chapter, section one presents a brief background on the uses of GIS in environmental economics literature. This section does not discuss overall results and significance of studies, rather, it synthesizes how GIS has been used in data collection. Section two outlines my study area, sources of data and the quality of data used in my analysis. Finally, section three documents specific methods used to analyze project data including specific GIS tools and automation functions in ArcGIS 10's "Model Builder".

3.1 Background

Application of GIS in the larger resource economics field is extensive, ranging from land cover studies (Walls et al., 2015 and Smith, 2002), urban growth impacts (Huang et al., 2007; Irwin 2002; Appleton et al., 2002; Irwin, 2001), air, water and noise pollution (Din et al., 2001; Leggett and Bockstael, 2000 and Metz and Clark, 1997) and recreation demand studies (Jones et al., 2010, Bateman et al., 1999; Lovett et al., 1997). Moreover, since manually collecting data on environmental and aesthetic variables can be extremely time consuming and potentially inaccurate, GIS is particularly useful in informing hedonic models. Parmeter and Pope (2012) provide an overview of steps necessary to complete a hedonic study and GIS is identified as a paramount method used for digitizing housing sales and analyzing environmental shape files.

Geocoding, a method of transforming raw addresses into physical points on a map space, is a crucial first step in most all hedonic models. For example, Anselin and Gallo (2006) use geocoding to assign 115,732 housing sales, which were originally available in a raw, non-spatialized format, to their respective locations in four Californian counties. Due to the homes being situated in space, Anselin and Gallo were able to intersect the locations of the sales with other spatially dependent variable such as air quality and socioeconomic characteristics of the region. To estimate the impacts of dams, dam removal, and river restoration, Lewis et al. (2008) attach spatial coordinates to 7,876 homes in order to measure their relative distance to various dams and rivers in the area. Similar to geocoding, Walls et al. (2015) join a spatialized parcel dataset to addresses through a unique parcel identifier.

Buffers, zones around a feature on a map measured in units of distance (ESRI, 2015), allow environmental economist to systematically observe the variables residing within set distances of an observation. For example, Heintzelman and Tuttle (2012) employ buffers ranging from 0.5 miles to 10 miles around 1,903 different parcels to capture the number of wind turbines sitting at various ranges. By capturing data from within buffers, independent variables such as “number of turbines within X distance” and “at least 1 turbine within X distance” could be used in the hedonic analysis. Similarly, Price (2010) creates buffers of 0.1km, 0.5km, and 1km to capture the amount of mountain pine beetle damage that is observed from individual housing sales.

Beyond simple queries, proximity and size, GIS can be used to find more intricate calculations and parameters. In an attempt to explain wetland values in an urban setting, Mahan et al. (2000) use GIS to systematically discriminate between linear or non-linear wetlands. Geoghegan et al. (1997) use GIS to derive several different landscape features including the complexity of the landscape, convoluted or uniformed feature edges and the connectedness of land use types. Even more advanced functions of GIS leverage topography and land features. For example, Walls et al. (2015) use a digital elevation model (DEM) to create view sheds, areas observed by the human eye at some point given physical or topographical obstructions, of 246,029 housing sales in Missouri.

3.2 Study Area, Sources and Data Validity

My study area is limited to the Western Washington counties of Skagit, Lewis, Cowlitz, Wahkiakum, Jefferson, Pacific, Grays Harbor, Whatcom, Thurston, Clallam, Mason and San Juan. All 12 counties lie west of the Cascade Range and capture a total of 19,097 square miles. Washington, colloquially known as “the Evergreen Etate”, is home to 8,926,490 hectares of forest covering 52% of the state (Littell, 2010) and contains over 30 different tree species (Mosher and Lunnum, 2003). While containing ample forest cover, the study area also supports a total population of 1,023,609 people and 413,202 households according to the 2010 US Census (2010). Seattle is among the fastest growing major cities in the US (Cohen et al., 2015), increasing human pressure on the forested environment and the associated ecosystems in the surrounding counties. These interactions, otherwise known as “wildland-urban interfaces” (Radeloff, 2005), have seen an increase of 29.6% in Washington from 1990-2000 alone (Hammer, 2007) along with population growth of 21.1% during the same period (US Census Bureau, 2001).

There are three primary sources of data in this study: aerial surveys, housing sales data and national land cover data. Each of the datasets are gathered from different sources and processed by different methods. The following section explains the source of each dataset, how the data are collected and some discussion on their validity and potential shortcomings.

3.2.1 Aerial Surveys of Blight

Maps showing forest defoliation are provided by the US Forest Service and Washington Department of Natural Resources (WA Department of Natural Resources, 2014). The data are in polygon vector shapefile form and represents yearly defoliation caused by a host of blighting agents including beetles and fungi. The data set also contains bear, water, and wind damage, which I removed before analysis (see Figure 1).

Currently, most state and federal agencies, including Washington, utilize aerial surveys to find defoliation and convert observations into GIS shapefiles by year (Department of Natural Resources, 2013). In this way, managers are able to determine areas of interest, show temporal trends, and overlay other map features. Besides proving costly, there are inherent errors in aerial surveys. According to the Department of Natural Resources (DNR), observers are able to identify 70% of the disturbances within ¼ mile of its actual location (Department of Natural Resources, 2013). Typically, a survey will consist of two observers viewing blight under the flight path and sketching it. Before 2001, sketches were done on 1:100,000 paper maps, but starting in 2002, touchscreen pads were used. The metadata also discloses that the ability to ID individual agent types is “variable at best”. Upon comparing surveys to aerial photographs, it becomes apparent that polygons, drawn by the observers, can cover a much larger area than the actual stands themselves, sometimes overstating the total area. Conversely, individual defoliated stands may be missed by the surveyor if not clustered together.

There is a limited body of peer reviewed literature concerning the accuracy and effectiveness of aerial surveys. MacLean and MacKinnon (1996) set out to compare predetermined areas of damaged land with rates of detection using conventional aerial surveys in New Brunswick, Canada. The authors use between 222 and 235 fixed plats containing 5-20 trees and monitored them each year between 1984 and 1993. The health of each plat was cataloged into damage classes and compared to aerial survey data from the same locations. Results varied from year to year, but overall, underestimation was dominant, revealing 37% of the plats were underestimated while up to 7% overestimated. MacLean and MacKinnon (1996) reveal another interesting finding by using a log-linear regression model to measure the effects of various conditions on accuracy such as defoliation class and weather conditions. Results showed that defoliation class type, weather conditions and assessment period have statistically significant effects on accuracy, as did an interaction between class-type and weather. Practically, results show that accuracy could be improved by controlling for weather and further varies with defoliator type.

Due to the variable accuracy found in aerial surveys, scientist have explored the use of airborne and satellite remote sensing technologies to indicate forest damage from various defoliators. Historically, the use of remotely sensed data has been expensive and of limited use due to low resolution images and the inability to distinguish defoliator types (Rullan-Silva et al. 2013). However, in recent years, more cost effective, finer resolution imagery has come online with the launch of MODIS and Earth Observing-1 among others (Melesse et al. 2007).

Since the advent of finer resolution imagery, a large body of literature has been published on its use in defoliation detection. Rullan-Silva et al. (2013) gather and compare recent literature on the subject, citing over 50 articles and explain the properties of remotely sensed data that make it useful in vegetation studies. Sensed data displays, among other things, the reflectance of an object along a continuous electromagnetic spectrum, known as a spectral signature. Spectral signatures are unique for many types of vegetation, and more importantly, will change as said vegetation becomes stressed. A key characteristics of the signature is that it spans both the visible portion of the spectrum as well as the non-visible, such as infrared. Reflection between healthy and stressed vegetation is more pronounced in the non-visible spectrum, therefore, their variation can be used by researchers for systematic detection (Rullan-Silva et al. 2013).

De Beurs and Townsend (2008) set out to determine a comprehensive model for damage detection by testing several different spectral indices. De Beurs and Townsend (2008) used NDVI (Normalized Difference Vegetation Index), and EVI (Enhanced Vegetation Index) among others such as the NDII (Normalized Difference Infrared Index). NDVI (see Equation 1) uses differences in red and near infrared reflectance bands of the electromagnetic spectrum to differentiate vegetation health (Rouse 1973).

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

Healthy plants typically absorb visible light (RED) for photosynthesis and reflects damaging near infrared light (NIR). As NIR reflectance increases and RED reflectance decreases in healthy plants, the equation above yeilds a higher number. By definition, the index is constrained between -1 and 1 with the healthiest trees reporting an NDVI above .8 and highly defoliated trees indicated by values close to 0 (Weier and Herring, 2000).

The EVI index used in de Beurs and Townsend (2008) paper is a similar index to the NDVI, where the NVI is an adjusted form to account for canopy background and atmospheric noise. In the EVI equation below (Equation 2), the RED band is adjusted by a new BLUE band along with various constants developed by Huete et al. (2002) to account for aerosol disturbances and canopy background adjustments.

$$EVI = 2.5 \times \frac{NIR-RED}{NIR+6\times RED-7.5\times BLUE+1} \quad (2)$$

For robustness, Beurs and Townsend (2008) also test the NDII for defoliation detection. The NDII uses the difference and ratio of near infrared and medium infrared reflectance to hone in on changes to water content in vegetation (Hunt and Rock 1989) (Equation 3).

$$NDII = \frac{NIR-MIR}{NIR+MIR} \quad (3)$$

Often time researchers use a non-defoliated base year to compare images. De Beurs and Townsend (2008) argue that this is not always useful, especially when extensive defoliation spans very many years. The literature also stresses that detection of defoliators can be inconsistent in the presence of fragmented forest and extreme topography. To isolate forest, the article uses the National Land Cover Database (NLCD) to mask off 117 plots in 2000 and 40 plots in 2001 that meet optimal conditions for detection. Results showed that using NDII performed most consistently in defoliation detection, with NDVI coming up second. A secondary analysis compares aerial sketch maps to index methods. This comparison showed that aerial surveys and indices are quite comparable, with the index method slightly over estimating defoliation.

More sophisticated methods of blight detection are possible using remote sensing in specialized cases, however aerial surveys currently offer the only complete set of blight data covering a national or large regional area (Gray and MacKinnon 2006). Furthermore, because of outdated sensors and lower resolution imagery, historical blight identification is likely to be restricted, inconsistent (Melesse et al. 2007) and does not exist as a widely usable form in my study area. These findings, combined with other literature discussed above (MacLean and MacKinnon 1996) demonstrate that the use of aerial surveys for this research will be necessary and adequate.

3.2.2 Housing Data

Housing sales data come from Real Market Data Inc., a company compiling county assessor and courthouse property data for Western Washington. The variables contained in the database include property price, structural variables such as floor area, bedrooms, bathrooms, age, lot acreage, buyer state and addresses from 1986-2012. The average home in the dataset is 43 years old, 1600sqft and contains 2.9 bedrooms. Twenty percent of the sales are said to have a view. It is useful to control for differences in information available to in-state and out-of-state buyers; using buyer zip codes, I determine that some 90% of buyers are “in-state” buyers.

To be useful in further analysis, housing data must be geocoded. As discussed in the literature section of this chapter, geocoding refers to the ability to transform raw addresses into physical points on a map space. For my purposes I used ESRI ArcGIS 10 to geocode since it has an ability to process large amounts of data at once (known as “batch geocoding”). It can be found in other programs and online services but it often has record limits, pay-per-record pricing, or is very time consuming. ArcGIS also allows its users to customize the match criteria and inspect record matches.

To geocode a table of addresses, a road system or parcel map that is already spatialized and containing address information is needed. A database of spatialized addresses, otherwise known as a “geocoder”, is cross referenced to match non-spatialized addresses to a geographic space. A road system, such as the U.S. Census “Tiger Lines” roads file (US Census Bureau, 2013) used for this research, is used to store a range of addresses for each segment of road. ArcGIS matches addresses from the data to the geocoder segment in the best fitting location based on a series of word recognition algorithms designed through years of mathematical literature (Goldberg, Wilson and Knoblock 2007).

There are inherent validity problems with geocoding, all of which I manage through due diligence. Many addresses within the housing sales data lack zip codes. In the geocoding process, ArcGIS uses zip codes to narrow the area to which it should search for a match. The absence of zip codes could direct the geocoder to mistakenly match duplicate addresses to the wrong counties. For example, multiple "15 Capitol St.'s" could exist in Washington; in which case, without zip code information, ArcGIS will arbitrarily pick one of several matches, rendering geocoding unreliable. To correct for this possibility, I separate all 13 counties to create individual county Geocoders. By running each county level address through their appropriate geocoder, I minimize the risk of one address being assigned to the wrong location with a similar name. During geocoding, each address match is given a score between 0 and 100, the user can then decide on which range of scores to accept and reject. Only allowing high scores will restrict the sample and not give flexibility to minor spelling and syntax errors, conversely, allowing low scores may allow false matches all together.

To exercise caution in score selection, I use a random sampling process to determine the errors present with a given level of geocoding sensitivity. I randomly pick 100 matches from the geocode at each level: 41-50, 51-60, 61-75, and 76-90 to test. My criteria for selecting an error hinges on 3 fields, street number, street name, and directional. If the match contains a completely different street number (i.e. 102 vs. 1002), I count it as an error. If the match contains a completely different name (i.e. Johnson vs. Joan), I count it as an error. And finally, if the directional prefix is completely misconstrued (i.e. NW vs. SE) I count it as an error. Matches that are clearly simple misspellings, punctuation differences or recording error I allow, as this flexibility is the purpose and strength of geocoding. After sifting through each categorical sample I find 32 errors in the 41-50 range, 27 in the 51-60 range, 3 in the 61-75 range, and none from 76-90.

After finding error rates in each sensitivity group, I calculate the error percentage of the whole population at various levels of sensitivity. Total population errors in turn measure 0.73%, 0.68%, 0.54% and 0% respectively (See Table 2).[1] It is also worth noting that the volume of records is not the constant across categories. There are far fewer observations in the 41-50 category (400) than in the 51-60 category (2,000), and far fewer observation in the 51-60 category than the 61-75 category (38,492) (Table 3).

Table 2: Errors within Ranges

Score Range	Errors/100	Error in total population
76-90	0	-
61-75	4	0.54%
51-60	18	0.68%
41-50	35	0.73%

[1] See appendix for error equations.

Table 3: Observation per Allowed Score Criteria

Allowed Scores	Percent Matched at given level	Addresses Remaining	# Of records in each category
>90	17.55%	56,971	56,971
>76	75.37%	244,676	187,705
>61	87.23%	283,168	38,492
>51	87.93%	285,432	2,264
>41	88.06%	285,859	427

As summarized in Table 3, errors dramatically decrease above the sensitivity of 61 and dropping observations at lower levels will not have a significant impact the total sample size. Consequently, I include all geocoded addresses that receive a score of 61 or higher. After geocoding and further cleanup, the final shapefile consists of 170,141 geocoded single family home sales in 12 western Washington counties over 26 years (Figure 2).

3.2.1 National Land Cover Database

National Land Cover Data (NLCD), provided by the United States Geological Survey (USGS), is a raster containing 16 different land cover classifications at 30 meter resolution. Because the NLCD has been updated 3 times since its original release in 1992, I gather cover from 1992, 1996, 2001 and 2011. This analysis is primarily concerned with forest cover, thus, cover codes 41, 42 and 43 which correspond to deciduous, evergreen and mixed types are queried out of the raster. For more useful analysis, the NLCD derived forest cover is converted to polygon vectors in ArcGIS 10.3 using the "raster to polygon" tool. Derived from remotely sensed data, the 2011 NLCD is estimated to be 91% accurate at the Anderson 2 level (Jin et al. 2013), while 1992, 2001 and 2006 NLCD reported 60%, 79% and 78% accuracy respectively (Wickham et al. 2013).

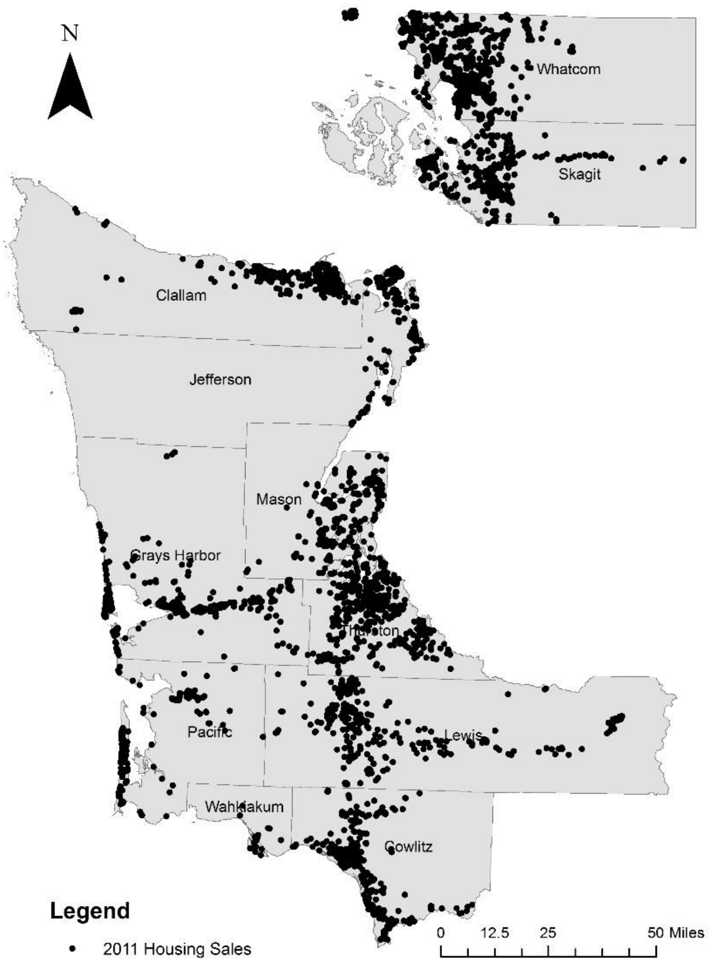

Figure 2: 2011 Geocoded Sales

3.3 Methods

My research primarily uses GIS to spatialize and intersect housing sales with forest blight information. I employ GIS to prepare much of the data used in regression analyses. GIS incorporates spatial datasets, allowing me to layer through common coordinate systems and extract relationships between the features. Furthermore, GIS permits me to control for spatially correlated errors within regressions (Bateman et al. 2002). Beyond these core capabilities, GIS offers automation and documentation throughout the process for quick, reproducible results.

In the following section I show, step by step, how to compile and interact data within a GIS to produce a dataset describing the proximity, area and type of forest blight for all housing transactions (See Figure 3). This section also shows the steps used to generate control variables such as a sale's census block and forested acres.

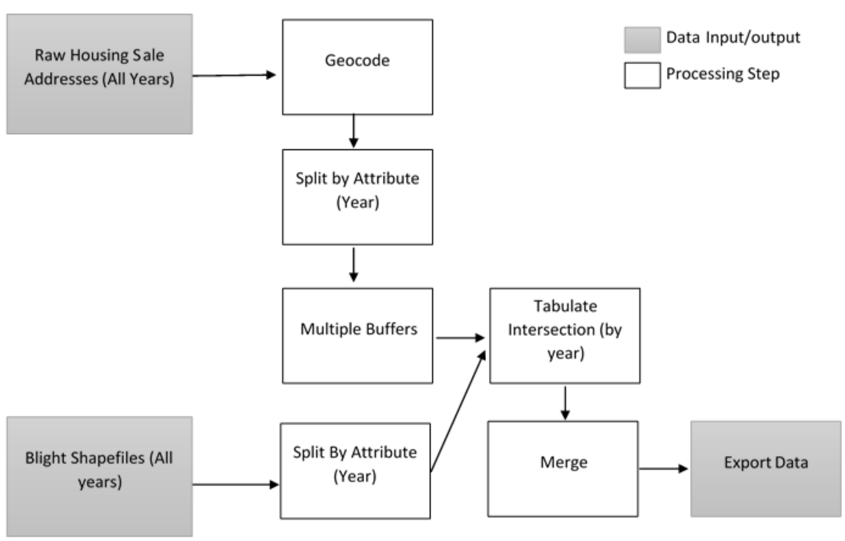

Figure 3: GIS Workflow

3.3.1 Splitting Data

A simple, yet integral step within the GIS is to split both the blight data and the housing sale shape files[2] into pieces, using their "year" attribute as identifiers. Blight itself is not necessarily a permanent fixture on the landscape; damaged areas, captured by aerial surveys one year, may be remedied in the following year. Similarly, a forest recorded one year as healthy could be defoliated just one year later. Splitting the data (see Figure 4), both housing sales and blight data by year allows for each specific year of sales to be interacted with its corresponding aerial survey data.[3]

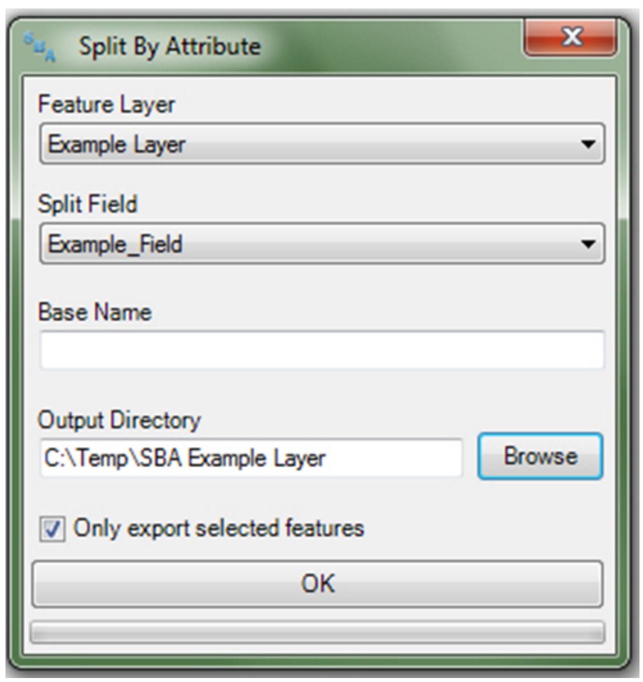

Figure 4: Split by Attribute Tool

GIS programs such as ArcGIS 10.3 has limited functionality to split a shapefile based on attribute field clusters. One approach is to query data and export new

[2] See housing data section for a discussion on geocoding
[3] At this stage, I be sure to include a unique identifier number for each sale.

shapefiles after each selection, however, depending on the number of query's needed, this process can be cumbersome. Alternatively, the United States Geological Service (USGS) has published a tool entitled "Split by Attribute" (Fox, 2015) that works within the ArcGIS 10 platform. By inputting a feature layer and designating a field title, the tool will produce a series of feature classes into any designated folder (see Figure 4).

3.3.2 Buffers and Intersections

A primary function of GIS in this research is to create a series of proximities, otherwise known as buffers, to intersect with blight polygons. Buffers serve as a useful way to capture any data from other layers that fall within their boundaries. To create various nested buffers around each sale, I use the "Multiple Buffers" tool in ArgGIS 10.3. There is no buffer size around a home in the blight literature that is determined as optimal, however some suggest ranges from 0.1km to 1km (Price 2010). In reality, the buffer size should be chosen by the researcher to answer the primary questions of the study. This paper attempts to expand the literature by examining externalities beyond what is previously considered. Consequently, I chose to define multiple nested buffers of 0.5km, 1km, 3km, and 5km.

To capture the blight data that falls within the aforementioned buffers, I use the tabulate intersect tool in ArcGIS 10.3. Tabulate intersection defines a zone (buffer) and a class (blight) feature then calculates how much of the class lay within the zone. Outputs of the tool can be varied such as acres, sq. miles, sq. kilometers etc. Because I geo-process individual years and intersect them with different buffer sizes, database output is ultimately structured in a year-by-buffer format. To combine outputs into one cohesive data set, I use the "Merge" tool and export the data into Excel using the "table to excel" tool.

Below is an example of the data produced when examining a single blight polygon intersected by different buffers. Highlighted in Figure 13, the 1km buffer fully capture the blight polygon. However, the 0.5km buffer only captures roughly half of the blight (see Figure 5). Table 4, an example of the data output of the workflow discussed above, confirms that 100% of blight polygon 8789 is captured within 1km buffers, while the 0.5km buffer intersects 48% of the blight or .97acres.

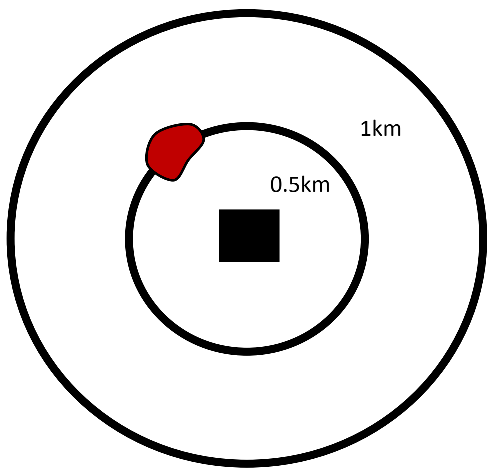

Figure 5: Visual Blight Intersection Example

Table 4: Table View- One Blight ID Intersected by 3 Buffers

Housing ID	Buffer Size	Blight ID	Agent	Blight Acres	% Intersected
23047	1km	8789	Fir Engraver	2.009	100
23047	0.5km	8789	Fir Engraver	.97	48

3.3.3 Process Automation

I use Esri ArcGIS 10.3 model builder to automate much of the geo-processing. Model Builder, a visual programming language (ESRI, 2015) that can run lengthy, complicated workflows automatically. Model builder works by providing an interface that can be populated by data, tools, and custom built modules. As data and tools are added, they can be connected in the same order that they would otherwise be processed in ArcMap. Once the model is built, different data inputs can be easily changed, as can tool parameters. Another advantage of the model builder environment is that the whole workflow can be copied and pasted into either the same environment or a separate standalone model.

Figure 6 provides an example of how model builder is used to automate the most repetitive portions of the GIS workflow. Starting on the left, I connect 2012 sales (data represented in blue ovals) to four different buffer tools (tools represented in orange rectangles) which produces 0.5km, 1km, 3km, 5km buffers around 2012 sales (tool outputs represented by green ovals). Next I connect the buffers to the tabulate intersection tool with blight data in 2012. Finally, I use the “table to excel” tool to export the attribute table of each shape file to Excel. I ultimately merge all Excel sheets into one file. Merging can also be accomplished in model builder using the “Merge” tool.

3.3.4 Other Geo-processing

Aside from using GIS to handle interactions between sales and blight, I derived a handful of other variables from GIS using similar techniques. An important variable that is used to control for spatial dependencies (see methods) is the census block that a sale resides in. To designate a block, I simply intersect a census block shape file (US Census Bureau, 2013) with the sales shapefile using the intersect tool. Sales are determined to be inside or outside of a city in the exact same way.

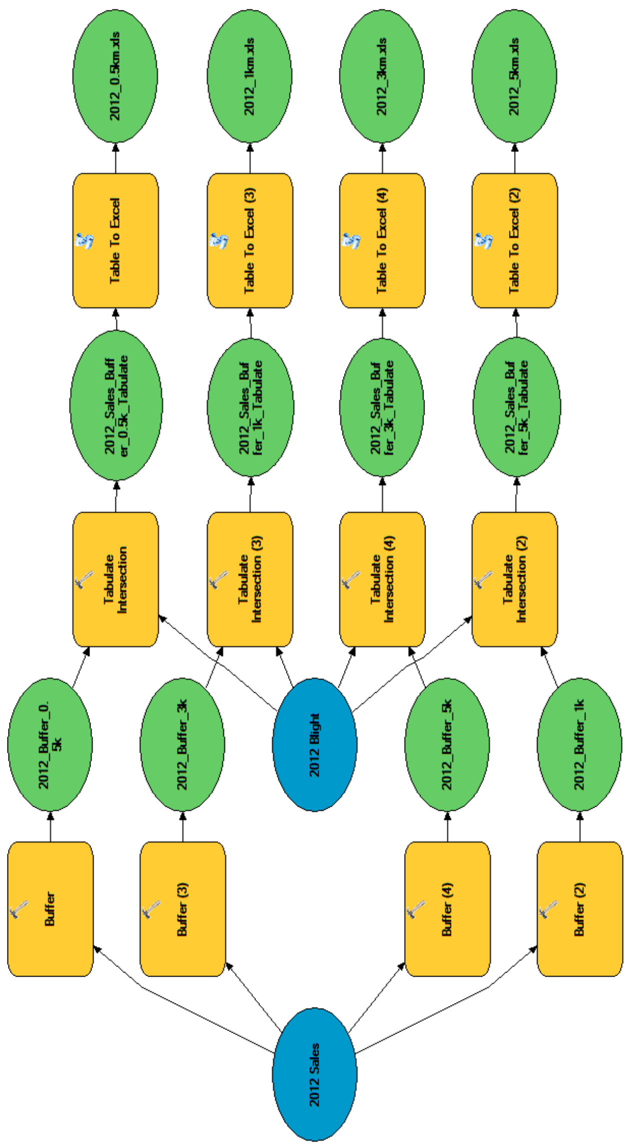

Figure 6: Example of Model Builder for GIS Workflow

Similar to the steps used for the creating blight variables above, the amount of forest cover captured by each buffer is also derived in GIS. It is common practice to use the National Land Cover Data (NLCD) to describe forest and other land cover characteristics for economic study (Walls 2015). The NLCD is a raster derived from satellite imagery (Jin et al. 2013), meaning that it is comprised of uniform pixels as opposed to polygons or "vector" data. Processing raster data require techniques that differ from vector techniques. For consistency, I transform the NLCD into a vector shapefile using the ArcMap tool "Raster to Polygon". Once NLCD polygons are created, I query for deciduous, evergreen and mixed forest types then run a model similar to the one in Figure 12 to tabulate their intersections with sale buffers. Because the NLCD is available for 4 different years (See NLCD section above), I intersect housing sales with the NLCD that is temporally closest to the sale (See Table 5).

Table 5: NLCD Year Assigned to Sales Ranges

NLCD Year	Sale Range
1992	86'-93'
1996	94'-98'
2001	99'-05'
2011	06'-12'

CHAPTER 4
JOURNAL ARTICLE

The Economic Impacts of Forest Pathogens in Washington State: A Hedonic Approach

Logan Blair *

Abstract

An increase in the incidence of forest pathogens in the Western US has created new resource management issues. In this research I employ a dataset of 170,141 housing transactions in twelve Western Washington counties to quantify the impacts of parasitic forest damage on the proxy real estate market. Specifically, I estimate a set of hedonic fixed effects models to control for omitted variable bias and spatial autocorrelation. Results show statistically significant impacts on property values in the presence of species specific and aggregate defoliation, suggesting new information for forestry management and policy.

Keywords: Hedonic, Environmental Economics, Revealed Preference, Environmental Impact, Forest

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*Logan Blair is a Masters Student in the Resource Management Program at Central Washington University. The views expressed in this paper are his own and do not represent those mentioned above.

4.1 Introduction

Whether for recreation, aesthetics, or bequeathment, forests hold special value to societies around the world. For western Washington, the value of this environmental amenity may be threatened as forest insects and other defoliators reach epidemic levels. While normal populations of native species are integral to the natural process of thinning weak, damaged stands in a forest environment (Winder and Shamoun, 2006), Washington State has experienced elevated defoliation in the past few decades. According to Washington Department of Natural Resources, pathogen-related forest damage has doubled since the 1980's and encompasses some 1.08 million acres in 2012 (Dozic et al. 2012) (see Figure 7). Other studies confirm that tree mortality in the Northwest has doubled every 17 years since 1955, in part due to pathogenic activity (Mantgem et al. 2009).

Forest disturbances in Washington State can be attributed to several factors. Decades of silvicultural practices and fire suppression have contributed to a substantially overstocked forest (Hessburg et al. 1994). Dense forests, containing greater species uniformity, provide a catalyst for rapid growth and defoliator spread, especially in drought years (Bentz et al. 2010). Crowded conditions can also invite various root diseases which weaken stands that are otherwise resilient to attack (Hessburg et al. 1994). Accompanying density, climate change may also exacerbate blight growth in northwestern US forests. Although a full discussion of climate change in the Pacific Northwest is beyond the scope of this work, entomological research suggests that forest insects in this region, particularly bark beetle, respond positively to warmer temperatures (Bentz et al. 2010). According to Bentz and others (2010), some defoliator species take several years to produce a single generation depending on the climate; as temperatures increase, this rate of reproduction also increases. Normal defoliator mortality rates also decrease due to warm temperatures (Régnière and Bentz 2007). Thus, in the face of increased forest density and climatic change, more volatility in even native species loads has become an increasingly important topic in forest management.[1]

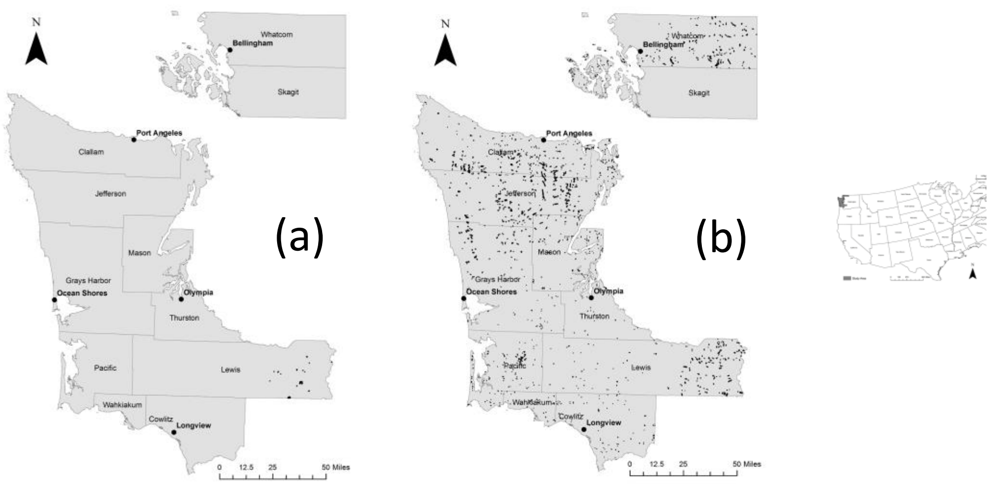

Figure 7: Blight in Western Washington: 1986 (a) and 2012 (b)

Forest damage in Washington State, and hence this study, is not limited to any single species. The Douglas Fir Beetle (*Dendroctonus pseudotsugae Hopkins*), which attacks the Douglas fir (*Pseudotsuga menziesii*) is known to serve as a thinning agent for

[1] See Lundquist and Bentz (2009) for a general discussion on bark beetles, climate change and management implications

already weak and damaged trees, but epidemic levels of the beetle can lead to attacks on otherwise healthy hosts (Schmitz and Gibson 1996) . The Douglas Fir Beetle has killed an estimated 27,000 acres in 2014 (Dozic et al., 2015). Similarly, the Pine Beetles (*Dendroctonus ponderosae Hopkins, Dendroctonus brevicomis LeConte & Ips spp*.) caused mortality in over 143,000 acres in 2014. Fir Engraver (*Scolytus ventralis*), considered a secondary pest that only attack stressed trees, can attack during existing outbreaks of other species or in drought ridden and overcrowded forest. In Washington, 31,000 acres were estimated to be killed by the fir engraver in 2014 (Dozic et al., 2015). Characterized by their naturally peeling copper color bark, Pacific Madrone (*Arbutus menaies*) have been declining since the 60's in the Pacific Northwest, especially in urban settings. While research concerning the causes of madrone decline is ongoing, several different canker and fungi have been found to cause damage including *Nattrassia mangifera and Fusicoccum aesculi* (Elliot et al. 2002). As many agents attack one type of tree, the Western Spruce Budworm (*Choristoneura occidentalis*) causes damage to the widest variety of tree stands ranging from 15 different firs and pines including the Douglas fir, Grand fir, Ponderosa pine, Limber pine, and ornamental trees like the Norway and Scotch pine (Fellin, 1992). Not all damaging agents in Washington fall under the insect category. White Pine Blister Rust (*Cronartium ribicola*) spores attach to the white pine (*Pinus strobus*) needles, eventually causing cankers and tree stand death (Dekker-Robertson et al. 2015). Dekker-Robertson (2013) estimated that 5 million cubic feet of white pine is lost in the Pacific Northwest annually due to the disease. Various root diseases including Annosum root disease (*Heterobasidion annosum*), Brown cubical butt rot (*Polyporus schweinitzii*), Tomentosus (*Inonotus tomentosus*), Laminated root rot (*Phellinus weirii*), and Armillaria root disease (*Armillaria mellea*) all significantly contribute to stand mortality in almost all tree varieties, particularly the Douglas fir and mountain hemlock (Hessburg et al. 1994).

Currently, national management plans such as the US Forest Service National Strategic Framework for Invasive Species Management (USDA, 2013) and the Western Bark Beetle Strategy (U.S. Forest Service, 2011) identify threats and prioritize efforts; however, such strategies come at great cost. For example, in 2011, the Forest Service budgeted $101.5 million for Bark Beetle control alone, with similar levels of funding to be appropriated through 2016 (U.S. Forest Service, 2011; USDA 2013). To maximize effectiveness and justify its efforts, the Forest Service is very clear that the best science should be considered to prioritize activities by, among other things, socio-economic impacts (USDA, 2013). Scientific research groups such as the Western Bark Beetle Research Group have also been formed by the USDA to study the entomological and other "application-motivated" work to help inform best management practices.

At a regional level, the Washington Invasive Species Council, formed in 2006, combines the efforts of multiple state and federal agencies. The council is charged with developing baselines, plans and recommendations focused on prevention and treatment of local infestations. In 2008, the Council developed a 20-year Strategic Plan to address the above mandate. Within this plan, the Council calls for economic modeling to help inform prioritization (Washington Invasive Species Council, 2008). While many environmental externalities, such as air and water pollution, spill over into the national or global arena, the effects of forest damage are relatively localized and thus easier to manage. However, the information needed to properly manage externalities is currently limited. While management can leverage market values, such as timber products and explicit fire damage, for traditional cost benefit analysis (USDA, 2013; U.S. Forest Service, 2011), impacts to any non-market environmental services poses externalities beyond classical markets, especially where heavy wild land-urban interface (WUI) exist (Holmes et. al 2010). Therefore, as management strategies evolve, it is important to support them with complete market as well as non-market information.

Hedonic real estate models attempt to quantify the aforementioned non-market values by observing the willingness to pay for a home at the time of sale given its structural and environmental qualities. Generally, single family parcels cannot be used for logging or commercial purposes. Therefore, the value of forest health derived from the hedonic function is connected to buyers' personal preferences, influenced by aesthetic consideration, recreational use, privacy, blocking eyesores, etc., and is separate from profitmaking associated with lumber harvest. In this way, society "reveals" its non-market valuation of forests.

With the exception of Payne et al. (1973), who use early hedonic methods, most older studies use either survey based contingent valuation (CVM), recreational values, or travel cost methods (TCM) to measure forest health and public welfare. Analyzing campsites that contain Douglas fir Tussock moth damage, Wickman and Renton (1975) estimate a recreational loss in California of $216 per affected campsite. Similarly, by comparing campground attendance between affected and unaffected park attendance in the Targhee National Park, Michalson (1975) finds consumer surplus losses of $510,362 and Leusher and Young (1978) find losses of $1,332,400 in east Texas campsites when compared to their healthier counterparts.

Between 1981 and 1990, Walsh and others (see Walsh and Olienyk 1981, Walsh et al. 1981, 1990, and Loomis and Walsh 1988) published a series of novel papers focused on the economic impacts of pine beetle and spruce budworm damage in the Colorado Rocky Mountains. Using travel cost and contingent valuation methods, authors find that, for a 15 percent decrease in forest health, recreational consumer surplus drops $11.60 per person (1981), and negative real estate impacts approach $896-$907. Walsh and others (1990) ultimately find that the average annual willingness to pay for forest protection is $52 per household.

Using surveys, numerous studies present how much the public is willing to pay to protect forests, with a wide-range of results depending upon program nature and geographic region. Asking households their willingness-to-pay for blight control, Jakus and Smith (1991) find that households would pay $348-$474 in the north-central Maryland and south-central Pennsylvania areas depending on whether it was private or public program. Haefele et al. (1992) find a willingness to pay of $103 for increased forest quality in the Southern Appalachian Mountains. Miller and Lindsay (1993) find consistent CVM willingness to pay results in New Hampshire of $43 to $70 for gypsy moth control programs. Finally, Holmes and Kramer (1996) use CVM to elicit an annual willingness to pay of $11-$36 per person to help protect the health of forest in and near the Great Smoky Mountains National Park. By using contingent survey methods, Kramer et al. (2003) estimates a willingness to pay of $28 per person to reduce forest damage in the Appalachian Mountains. Additionally, a market-based analysis of the timber industry has found a willingness to pay of up to $2,530 to mitigate the pine tip moth from 400 Nantucket Pines (Asero, Carter and Berisford 2006).

Hedonic property methods, which use real estate price fluctuations in the face of changing forest health as a measuring stick for societal impacts, have become most popular in recent literature. Thompson et al. (1999) attempt to quantify the impact of insect damage on a small neighborhood in the Lake Tahoe Basin. This area features rather expensive real estate, with the average home valued at $334,000, and is surrounded by dense forest which had been heavily damaged by infections. The results show that the presence of forest blight can decrease the value of a median-priced Tahoe home by $26,390.

Price et al. (2010) focus on the mountain pine beetle’s (MPB) non-market impacts and the willingness to pay for mitigation using a hedonic real estate model in Grant County Colorado from 1996-2006. The study includes usual structural and area variables such as rooms, square feet, acres, block etc., as well as a treatment group, in this case, forest blight at different distances. To control for spatial autocorrelation, unaccounted-for homes nearby affecting the price on one another, the authors use spatially-weighted terms assigned by nearest neighbor. Results show that there are significant negative effects of blight ranging from -0.1%, -0.008%, and -0.003% per number of trees killed for 0.1, 0.5, and 1km distances, respectively. Accordingly, the paper finds the implicit price of a dead tree to be $648, $43 and $17. Even though this work is not conducted in Washington State, Price et al.'s (2010) results give general insight into the functional relationship that exists between property value and forest blight while advancing the applied use of GIS.

Other literature using hedonic models finds mixed or even positive impacts of forest defoliation. Holmes et al. (2006) estimate the effect of hemlock woolly adelgid infected hemlocks on housing values in Sparta, New Jersey. This study is particularly useful in that damaged trees are classified into different thresholds of damage as well as into different distances ranging from the parcel level to 1km beyond the parcel. This specification allows for comparison of different damage thresholds and tests whether impacts extend beyond parcels alone. The authors find evidence that moderate tree health negatively impacts residential value while severe damage was statistically insignificant and that fully dead hemlock yield positive impacts on real estate prices. As a justification for positive impacts, the authors cite possibilities such as additional light entering the forest and favorable new growth. This study lends important contributions to the literature by showing that property value may be contingent on different levels of blight severity, and, as in Price et al. (2010), that these effects can be induced from far beyond an individual parcel.

In a similar fashion to Holmes et al. (2006), Holmes et al. (2010) use both spatial and fixed effects hedonic models to estimate the impacts of woolly adelgid infected hemlock on house prices in West Milford, New Jersey. The authors employ remote sensing data to break up woolly adelgid outbreak into several damage categories ranging from healthy to dead, finding that, in general, outbreaks have significant negative impacts on real estate. Properties subjected to hemlock decline or damage experienced losses in value ranging from 1-1.6%.

Using several different spatial hedonic models, Hansen and Naughton (2013) estimate that spruce bark beetle outbreaks in south-central Alaska can increase assessed property values by 2.1% and 3.7% when damage occurs within 0.1 - 0.5km or 0.5 - 1.0km from a home. Properties in this region are close to dramatic ocean and mountain views. The authors suggest that pending views lend to the likelihood that the thinning effects of disturbance enhance views and outweigh any negative effects inherent to the disturbance itself.

Kovacs et al. (2011) attempt to predict the spread of sudden oak death (SOD) in California from 2010-2020, and estimate the total removal costs and property loss at 2020 levels. Primary results claim that, if forecast assumptions hold true, 10% of 734,000 oak trees on developed land will need to be treated or removed by 2020 at a cost of $7.5 million, and property will be reduced by up to $135 million. Hypothetically, if all 734,000 trees needed treatment or replacement it would cost $729 million and the loss of real estate value would top $8.3 billion.

Literature addressing the relationship between forest blight and housing values has produced results that are mixed and varying in magnitude. For example, communities in Lake Tahoe (Thompson et al., 1999) value forest differently than in southcentral Alaska (Hansen and Naughton, 2013) and all societies conceptually value forest health differently from year to year depending on economic health and changing social norms. Previous works have searched for impacts on parcels or proximities extending out to 1km in a relatively focused study area. Accordingly, literature emphasizes the need for larger geographical study areas and to expand the search for externalities as they exist beyond the parcel to facilitate more relevant regional policy and find more consistent estimates (Rosenberger et al. 2012).

This paper builds on existing literature in several ways (See Table 6). I investigate the impacts of forest blight across a sizable regional arena by employing, to my knowledge, the largest dataset seen in blight research, comprising of 172,119 western Washington housing transactions spanning 26 years. I extend the search for externalities beyond the parcel to a 5km radius, and estimate census block and repeat sales fixed effects models to avoid various forms of bias inherent in other hedonic models. Due to an expansive study area harboring several types of blighting agents, I present an analysis of their aggregate as well as select individual blight impacts. To offer an explanation of inconsistent results in recent literature, I suggest a non-linear relationship between forest blight and real estate values. Specifically, I find evidence that nearby small to moderate forest blight increases property values only to decrease them at the most severe coverages.

Table 6: Hedonic Studies of Forest Blight

Year	Study	Geographical Area	Number of Observations	Impacts
1973	Payne et al.	N/A	N/A	N/A
1999	Thompson et al.	84,240 ha	100	Negative
2006	Holmes et al.	39 sq. mi.	3379	Negative
2010	Holmes et al.	80 sq. mi.	4,373	Mixed
2010	Price et al.	4842 sq. km	3681	Negative
2013	Hansen and Naughton	N/A	8796	Positive
2015	Blair et al.	19,097 sq. mi	170,141	Mixed

The next section of this paper describes the study area and data that were used in modeling. Section three presents my methods, model specifications and empirical issues. Section four presents results and section five discusses them. Finally, section six suggests further work and concludes the study.

4.2 Study Area and Data

My study area is limited to the Western Washington counties of Skagit, Lewis, Cowlitz, Wahkiakum, Jefferson, Pacific, Grays Harbor, Whatcom, Thurston, Clallam, Mason and San Juan. All 12 counties lie west of the Cascade Range and capture a total 19,097 square miles. Washington is home to 8,926,490 hectares of forest covering 52% of the state (Littell, 2010) and contains over 30 different tree species (Mosher and Lunnum 2003). While containing ample forest cover, the study area also supports a total population of 1,023,609 people and 413,202 households according to the 2010 US

Census (2010). Seattle is among the fastest growing major cities (Cohen et al., 2015), increasing human pressure on the forested environment and the associated ecosystems in the surrounding counties. These interactions, otherwise known as "wildland-urban interfaces" (Radeloff, 2005), have seen an increase of 29.6% in Washington from 1990-2000 alone (Hammer et al., 2007) along with population growth of 21.1% during the same period (US Census Bureau, 2001).

There are three primary sources of data in this study: aerial surveys, housing sales data and national land cover data. Maps showing forest defoliation are provided by the US Forest Service (USFS) and Washington Department of Natural Resources (WADNR) (WA Department of Natural Resources, 2014) using data collected from aerial surveys. The maps contain polygons of varying sizes representing areas of blight denoted by species and year. Although defoliators are primarily insects and fungi, the survey also collects bear, water and wind damage, which I removed from the data. WADNR metadata suggest a survey accuracy of 70% while independent studies using similar techniques in New Brunswick, Canada suggest that aerial survey accuracy range from 56% - 82% depending on damage severity, type and weather conditions (MacLean and MacKinnon, 1996).

Housing sales data are obtained from Real Market Data, a company compiling county assessor and courthouse property data. The variables contained in the database include property price, structural variables such as floor area, bedrooms, bathrooms, age, lot acreage, buyer state and addresses from 1986-2012. The average home in the dataset is 43 years old. The average square footage of a home is 1600 and the average number of bedrooms is 2.9. Twenty percent of the sales are said to have a view. It is useful to control for differences in information presented to in-state and out-of-state buyers, therefore, buyer zip codes are used to determine that some 90% of the purchases fell into the “in-state” category.

To spatialize respective sales on a map, a technique called geocoding is used to match housing addresses to a map space. For this exercise, I use ESRI ArcMap 10. Although a full discussion of the geocoding algorithm is beyond the scope of this paper, I will discuss the measures taken to ensure geocoding accuracy and integrity within the dataset. ArcGIS contains a canned geocoding function which allows its users to upload address information in bulk to be cross referenced with existing digital street maps. For my purposes, I designated a U.S. Census “Tiger Lines” roads file (US Census Bureau, 2013) and geocoded addresses county by county to ensure address uniqueness. The geocoding function ranks each match on a scale from 0-100, where zero has no address information and 100 is a perfect match. To create an acceptable cut off score, 100 matches were chosen randomly from several match score categories (61-70, 71-80, 81-90, 91-100 etc.) and checked against the original data.[2] Ultimately, I accept match scores >61 which yields an overall 0.54% matching error while still retaining 87% of the original

[2] ESRI’s ArcMap geocoding function reports two addresses, the original input address, and the US Census Road Network address that its algorithm believes the input address matches with.

observations. After geocoding and further cleanup, the final data consist of 170,141 digitized single family home sales in 12 western Washington counties over 26 years.

To accurately derive real prices in such a geographically and temporally large data set, I retrieve nine separate All-Transaction Housing Indices retrieved from the St. Louis Federal Reserve (US. Federal Housing Finance Agency, 2014). If an available index corresponds to the observation's county, that index is used to normalize the sale price. If no index exists, I assigned one subject to county demographics and relevant industry. After adjustment, the mean price of a home in the data set is $145,437 normalized to 1995.

In order to extract blighted acres observed at various distances, I create 0.5, 1, 3 and 5km buffers around each geocoded sale in ArcGIS and intersect them with their corresponding WADNR forest disturbance map mentioned above. In a similar fashion, forest cover variables are generated by pairing each observation to one of four different National Land Cover Datasets (NLCD) ranging from 1992 to 2011 (Jin et al. 2013). In addition, 0.5 km, 1 km, 3 km, and 5 km buffers report an average of 0.1, 0.6, 4, and 15 acres of aggregate blight while the same buffers contain an average of 12, 220 and 1652 acres of forest cover respectively (see Table 7).[3]

[3] 3km forest cover is used for 5km models due to computational restrictions.

Table 7: Summary Statistics

	Variable	All Properties			Repeat Sales Properties		
		Mean	Std. Dev.	Treated	Mean	Std. Dev.	Treated
	Property Characteristics						
	Sale Price (Dollars)	145437	75742	-	139898	66621	-
	Acres	1.0	4.7	-	0.6	2.7	-
	View	0.2	0.4	-	0.1	0.4	-
	Local Buyer	0.9	0.3	-	0.9	0.3	-
	House Age (Years)	43.4	26.6	-	44.5	25.9	-
	Floor Area (Square feet.)	1600	585	-	1563	549	-
	Bedrooms	2.9	0.7	-	2.9	0.7	-
	City	0.5	0.49	-	0.53	0.49	-
	3km Forest Cover (Acres)	1652	1451	-	1574	1421	-
	1km Forest Cover (Acres)	220	431	-	204	400	-
	0.5km Forest Cover (Acres)	12.2	21	-	10	20	-
	Treatment Variables						
5km	Aggregate Blight	15	82	52020	13	79	27573
	Douglas-fir beetle	4.2	22.2	37156	3.7	20.9	19556
	Fir engraver	2.6	24.5	12343	2.2	22.2	5852
	Pacific madrone decline	3.3	26.9	8417	2.9	24.4	4473
	Other	5.1	67.8	15437	4.6	67.1	8103
3km	Aggregate Blight	4.0	37	22067	3.6	36.3	11098
	Douglas-fir beetle	0.8	8.2	13879	0.7	7.2	6918
	3km Fir engraver	0.6	9.7	4386	0.5	8.9	1974
	Pacific madrone decline	1.0	11.1	3858	0.9	9.7	2090
	Other	1.7	32.6	5436	1.5	32.7	2707
1km	Aggregate Blight	0.6	7.4	6663	0.5	7.0	3185
	Douglas-fir beetle	0.1	2.3	3625	0.1	2.0	1696
	Fir engraver	0.1	2.4	1459	0.1	2.0	657
	Pacific madrone decline	0.1	2.8	1067	0.1	2.6	552
	Other	0.2	6.0	1188	0.2	5.8	566
0.5km	Aggregate Blight	0.1	2.4	1838	0.1	2.2	890
	Douglas-fir beetle	0.0	0.7	758	0.0	0.5	366
	Fir engraver	0.0	0.9	311	0.0	0.7	134
	Pacific madrone decline	0.0	1.0	399	0.0	0.9	214
	Other	0.0	1.9	411	0.0	1.8	194

Note: All treatment variables in acres

4.3 Methods and Empirical Issues

This research is primarily concerned with measuring the impacts of blighted forest on the sale price of a home, holding all other factors that determine home prices constant. In theory, a home is a unique piece of capital whose price is determined through a group of structural, neighborhood, and other area characteristics including various environmental amenities and disamenities. In other words, homeowners buy a "bundle" of goods as opposed to one homogeneous product. Individuals may value real estate features differently, however, in a large market with many players and many competing goods it is assumed that the value of each heterogeneous commodity that makes up the housing bundle is ultimately explicitly defined (Rosen, 1974).[4] This utility function, explained originally by Rosen (1974), is otherwise known as a hedonic real estate price model:

$$p(z) = p(z_1, \ldots, z_n) \tag{8}$$

where p is the price of a home given z differentiated products of estimated fixed values. In the same way that size and quality of a home are widely accepted to impact price in the equation above, there may be evidence that consumers capitalize forest health into their real estate purchases. I hypothesize that, as forest blight area increase, its impacts on housing sale price will be different from zero. Formally, the null:

$$\mathrm{H}_0 : \beta_1 \text{ Blighted Forest} = 0$$

and it's alternative

[4] For more complete discussion of hedonic price theory and its history see Sheppard (1999).

$$H_1: \beta_1 \text{ Blighted Forest} \neq 0$$

Accurately testing the above relationship requires careful thought on when and how forest blight might affect the purchasing price of a home. Blight itself is not necessarily a permanent fixture on the landscape, nor can it be treated as such. Damaged areas, captured by aerial surveys one year, may be remedied in the following year. Similarly, a forest recorded one year as healthy could be defoliated just one year later. I interact each year of sales with corresponding aerial blight survey data in order to reduce the chance of a false treatment.

It is unrealistic to assume that homeowner utility changes when forest damage is present on personal property only. If buyers believe that unhealthy forest beyond their parcel could spread, pose a fire hazard or visually alter the landscape, impacts may spill over beyond private property and into the public realm (Price et al. 2008). Measuring the distance from a home to the nearest patch of blight might yield a simple interpretation of these externalities, however, it would ignore any variability in blighted acres. In contrast, measuring blighted acres within a single predetermined distance would miss the opportunity to observe how impacts change as blight extends beyond the parcel. To measure the impacts of both acreage and distance, I regress blight area (in acres) that is captured by four progressively larger "buffers" i.e. radii of 0.5 km, 1 km, 3 km, and 5 km around each parcel centroid on the natural log of sale price. I run each specification (see equation 2 and 3 below) separately to show the estimated effects of blighted acres as the buffer is expanded to capture blight polygons of various sizes.

Due to the large geographical and temporal scope of this study, many observations range from containing trivial amounts of a single blighting agent to nearly complete inundation by multiple types of damage and disease (See Table 7). To ensure that the impacts of critical forest defoliation can be differentiated from relatively normal occurrences or desirable forest thinning effects found in previous literature I include a quadratic specification to capture any nonlinear effects. In this way, the partial effects of blight on sale price can be charted. In addition to a model describing aggregate blight, I take advantage of its differentiation in the data by parsing the top four agents by volume and running them together in the same regression. Thus I am able to test whether or not people respond differently to specific species.

According to Greenstone and Gayer (2009) and Parmeter and Pope (2012), simple hedonic models are historically plagued by omitted variable bias. It is nearly impossible to control for all factors that impact the price of a home and if any omitted variables are correlated with included and dependent variables, bias occurs. Practically, consider homes near a good school. If data on bus traffic was included in the hedonic study and not the school itself, results might surprisingly show that bus traffic density raises real estate prices, when in reality the true effects are caused by the omitted school. A form of omitted variable bias, unique to this study, occurs when blight (treatment) is contingent on the level of a forest or wooded area near a parcel. As areas of blight increase, so can the amount of trees near a property. This codetermination means that if forest cover near an observation is not controlled for, blight could become a proxy for the omitted forest cover and bias its true impacts. To control for confounding forest cover variables, I use the National Land Cover Database (Jin et al. 2013) to assign forest cover characteristics to the model. In this way, similar to Price et al. (2010), forest cover is explicitly defined.

Similar to omitted variable bias, spatial autocorrelation can introduce bias when the features of one observation causes other observation features to take on specific characteristics (Dormann et al. 2007). This correlative relationship strictly violates statistical assumption that error terms are independently determined from one another and can be particularly damaging when analyzing markets over a large spatial scale. In my research, autocorrelation is apparent in the size, style, and quality of a home directly affecting similar features of their neighbors. Some hedonic studies concerning forest blight utilize a spatial weights matrix to address error term dependency, while Holmes et al. (2010) suggest that fixed-effects models are most efficient in addressing spatial dependency issues. In attempts to standardize hedonic methods, Kuminoff et al. (2010) argue that the use of spatial errors and spatial lag techniques used to purge models of bias have become “stylized facts” and find that they can actually underperform models with no spatial controls at all. After running a series of Monte Carlo replications, Kuminoff et al. (2010) find further evidence that using various levels of spatial fixed effects most efficiently controls for aforementioned bias. While Holmes et al. (2010) provide the only forest blight specific study which utilizes fixed effects to my knowledge, many other applied works (Walls, 2015; Guignet, 2013; Heintzelman and Alterieri, 2013;

Heintzelman and Tuttle, 2011) offer practical examples of spatial fixed effects techniques, otherwise void from forest blight research. Therefore, given the recent mounting evidence in favor of fixed effects specifications, I depart from the larger hedonic blight literature and follow the empirical suggestions by Parmeter and Pope (2012), Kuminoff et al. (2010) and the applied work that supports them.

Fixed-effects control for spatially correlated errors and variation in housing prices caused by unknown factors in the usual OLS regression by assigning geographical indicator variables (Parameter and Pope 2012). By doing so, each indicator variable controls for any variation in home values unique to that spatial group. Following Heintzelman and Tuttle (2011), I include a vector of indicator variables for each spatially grouped set of observations, in this case, census block. Furthermore, I interact sale year and block dummies to control for census block characteristics changing over time (Kuminoff et al. 2010). Fixed effects models will also address spatial autocorrelation. As discussed by Dormann et al. (2007), if observations are geographically categorized, autocorrelation will be restrained by only allowing error correlations within the specified area. In the models below, I assign all transactions within a unique geographic classification (i.e. census block) along with a unique error term for that group.

There are clear advantages and disadvantages to repeat sale and pooled models. The repeat sales model observes variation within a specific property as it is sold over time. This is advantageous in strictly controlling for omitted variables unique to a home itself and any other time-invariant factors. However, more control potentially restricts overall variation and reduces explanatory power. Since only repeatedly sold properties can be used, often times the parcel fixed effects model also dramatically reduces sample size and is in danger of selecting only observations that exhibit characteristics desirable for resale. Fortunately, the size and temporal scope of my data allows for 100,231 repeat sales or 59% of the original data. Table 7 shows that key variables generally maintain similar figures between the two data sets. Pooled regression models, in this case executed as a census block fixed effects model, lose some control over omitted variables and autocorrelation but gain variation and the ability to use the full dataset. In both cases, I determine the percent change in housing price Y given some amount of blight X multiplied by its estimated coefficients β_1 and β_2. The block fixed effects regression equation for parcel i in block j at time period t:

$$ln\mathrm{Y}_{\mathrm{ijt}} = \beta_1\mathrm{X}_{\mathrm{ijt}} + \beta_2{\mathrm{X}_{\mathrm{ijt}}}^2 + \beta_3\mathrm{W}_{\mathrm{it}} + \alpha_{\mathrm{j}} \times \lambda_{\mathrm{t}} + \rho_{jt} + \mathrm{u}_{\mathrm{ijt}} \tag{9}$$

In equation (2), $\ln\mathrm{Y}_{\mathrm{ijt}}$ is the log price of home i in census block j at time t. $\mathrm{X}_{\mathrm{ijt}}$ represents forest blight in acres and ${\mathrm{X}_{\mathrm{ijt}}}^2$ is the quadratic form of blighted acres. W_{it} includes a series of structural housing variables such as square feet and rooms as well as environmental controls like forest cover and whether or not the sale occurred within a city. α_{j} is a vector of census block fixed effects; λ_{t} contains year dummies and ρ_{jt} represents a clustered error term for each block along with the individual errors $\mathrm{u}_{\mathrm{ijt}}$.

The repeat sales regression equation for parcel i at time period t:

$$ln\mathrm{Y}_{\mathrm{it}} = \beta_1\mathrm{X}_{\mathrm{it}} + \beta_2{\mathrm{X}_{\mathrm{it}}}^2 + \beta_3\mathrm{W}_{\mathrm{it}} + \alpha_{\mathrm{i}} + \lambda_{\mathrm{t}} + \mathrm{u}_{\mathrm{it}} \tag{10}$$

In the repeat sales model, $ln\mathrm{Y}_{\mathrm{it}}$ is the log price of home i at time t . X_{it} represents blighted acres, and $\mathrm{X}_{\mathrm{it}}{}^{2}$ is the quadratic form of blighted acres. Since structural attributes within an individual parcel such as bedrooms and square feet generally do not change as the same home is sold repeatedly, W_{it} contains only housing characteristics that vary with time such as house age and local buyer. α_{i} represents a vector of repeatedly sold parcels. λ_{t} represents year fixed effects and u_{it} is the usual error term. I will ultimately employ both models, pooled and repeat sales, and report their results separately to ensure robustness and transparency.

4.4 Results

Table 8 displays the primary results of the study from eight aggregate blight models[5]. Each result represents a specific buffer size and either a pooled census block (Model 1, 3, 5, and 7) or repeat sales fixed effects model (Model 2, 4, 6 and 8). With the exception of the 0.5km repeat sales model, results show significant coefficient estimates on the quadratic form in all models suggesting that aggregate blight impacts on price are parabolic whose shape increases at a decreasing rate. In other words, housing prices are positively impacted in respects to low levels of affected acres, begin to decline at moderate levels, and become negative at high levels.

Beyond a general nonlinear relationship, the magnitude and point at which negative impacts are realized depend on the amount of aggregate blighted acres and

[5] Regression coefficients are estimated using the statistical software R in conjunction with the lfe package (Gaure, 2014) for grouped fixed effects and stargazer (Hlavac, 2014) for table production.

their proximity to a sale. I use the results from pooled and repeat sales models to plug in values of aggregate blight acres from the data, and examine their partial effects on price.[6] Starting with pooled models, the analysis shows that blighted forest within 3km and 5km from a sale demonstrate similar elasticities in respect to sale prices. At the mean acres of blighted forest, both the 3km and 5km models estimate a positive 2% impact on price.[7] One standard deviation from the mean offers a general turning point, while two to three standard deviations from the mean yield an estimated -2% to -3% loss in value. Blighted acres specifically within 1km of a sale offer a more dramatic result. At mean levels, positive impacts are estimated to be 19% and one standard deviation from the mean yields almost zero impact. However, two to three standard deviations from the mean result in a -10% to -25% reduction in price. Defoliation occurring exclusively within 0.5km of a sale yields largely positive results showing sale price positively impacted until levels reach two standard deviation from the mean, beyond which, impacts are slightly negative.

Repeat sales models seem to yield results with lower estimated impact magnitudes, but generally consistent directions of estimated relationship to that of the pooled models. The 5km repeat sales model estimates a positive impact of 1% across all reasonable data inputs[8], 3km models report positive 1% impacts at the mean and -1%

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[6] Pooled census block models are used as they provide the most consistent results across all specifications.

[7] All means and standard deviations used to find price elasticities are calculated from blighted properties within each specified buffer size.

[8] Reasonable inputs include blighted acres within 3 standard deviations from the mean. More extreme values in the data yield larger negative elasticities but are not representative of the sample.

impacts three standard deviations from the mean while the 1km model reports positive 8% impacts at the mean with those effect diminishing to zero three deviations from the mean. The repeat sales model examining blight impacts at 0.5 km is approaching significance and interesting in reporting partial effects of 12% and -1% impacts at the blight mean and 3 standard deviations from the mean respectively.

Table 8: Hedonic Regression Results – Aggregate Blight

	0.5km		1km		3km		5km	
Dependent Variable = ln(Sale Price)	Pooled (1)	Repeat Sales (2)	Pooled (3)	Repeat Sales (4)	Pooled (5)	Repeat Sales (6)	Pooled (7)	Repeat Sales (8)
Blight (10 acres)	0.054***	0.012	0.020***	0.008***	0.002***	0.001**	0.002***	0.001***
	(0.008)	(0.009)	(0.003)	(0.002)	(0.0007)	(0.0005)	(0.0003)	(0.0002)
Blight Squared (10 acres)	-0.004***	-0.001	-0.001***	-0.0002***	-0.00002***	-0.00001*	-0.00001***	-0.00003***
	(0.001)	(0.0006)	(0.0001)	(0.00005)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Acres	0.014***	-	0.014***	-	0.013***	-	0.013***	-
	(0.0005)		(0.0005)		(0.0005)		(0.0005)	
View	0.174***	-	0.170***	-	0.166***	-	0.164***	-
	(0.005)		(0.005)		(0.005)		(0.005)	
Floor Area (100 ft2)	0.036***	-	0.036***	-	0.036***	-	0.036***	-
	(0.0006)		(0.0006)		(0.0006)		(0.0006)	
Bedrooms	-0.023***	-	-0.023***	-	-0.022***	-	-0.022***	-
	(0.003)		(0.003)		(0.003)		(0.001)	
City	-0.035***	-	-0.036***	-	-0.041***	-	-0.041***	-
	(0.006)		(0.006)		(0.006)		(0.006)	
Forest Cover (10 acres)	0.007***	-	0.001***	-	0.0002***	-	0.0002***	-
	(0.001)		(0.00005)		(0.00002)		(0.00002)	
Local Buyer	-0.096***	-0.025***	-0.094***	-0.025***	-0.093***	-0.025***	-0.092***	-0.025***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
House Age (10 years)	-0.031***	-0.094***	-0.030***	-0.094***	-0.031***	-0.094***	-0.031***	-0.094***
	(0.003)	(0.03)	(0.003)	(0.03)	(0.003)	(0.03)	(0.003)	(0.003)
House Age Squared (10 years)	0.002***	0.007***	0.002***	0.007***	0.002***	0.007***	0.002***	0.007***
	(0.0002)	(0.002)	(0.0002)	(0.002)	(0.0002)	(0.002)	(0.0002)	(0.002)
Observations	170,141	100,231	170,141	100,231	170,141	100,231	170,141	100,231
Adjusted R^2	0.473	0.883	0.475	0.883	0.477	0.883	0.478	0.883
Year × Census Block FE	Yes	No	Yes	No	Yes	No	Yes	No
Property and Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: *p<0.1** p<0.05***p<0.01

The effects of individual forest pathogens are somewhat mixed. Table 9 displays eight models representing the impacts of Douglas fir beetle, fir engraver, pacific madrone decline and an ”other” category[9]. As in Table 8, each result represents a specific buffer size and either a pooled census block (Model 1, 3, 5, and 7) or property fixed effects model (Model 2, 4, 6 and 8). Similar to aggregate blight model results above, all pooled models focused on Douglas fir beetle damage show significant nonlinear impacts ranging from positive to negative depending on affected acres. Douglas fir beetle repeat sales models are not significant. With the exception of the 0.5km buffer, Fir Engraver models exhibit significant nonlinear impacts at the block and parcel fixed effects levels. Similar to Douglas fir beetle impacts, Pacific madrone decline yields diminishing positive impacts in the block fixed effects model and mixed results in the repeat sales models. Interestingly, the 0.5 and 1.0km “other” block models yield significant negative linear impacts with an insignificant quadratic term. 1 and 3km “other” block models show significant non-linear impacts that decrease at an increasing rate. All “other” category results are insignificant in repeat sales models.

[9] Other category includes: Root disease, Spruce aphid, Hardwood decline, Swiss needle cast, Spruce beetle, Mountain pine beetle, Leaf Rust in Poplars, Lodgepole needle cast, Douglas-fir engraver, Port-Orford-Cedar Root Disease, Black pineleaf scale, Balsam woolly adelgid, Dying hemlock, Mountain pine beetle, Douglas-fir tussock moth, Western hemlock looper, Silver fir beetles, Western balsam bark beetle, Western pine beetle, Mountain pine beetle, Douglas-fir Budmoth and White pine blister rust.

Table 9: Hedonic Regression Results – Blight Category

	0.5km		1km		3km		5km	
Dependent Variable = ln(Sale Price)	Pooled (1)	Repeat Sales (2)	Pooled (3)	Repeat Sales (4)	Pooled (5)	Repeat Sales (6)	Pooled (7)	Repeat Sales (8)
Douglas fir Beetle	0.148***	-0.016	0.044***	0.003	0.013***	-0.003	0.015***	0.001
	(0.028)	(0.039)	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Douglas fir Beetle Squared	-0.014***	0.015	-0.001***	0.002	-0.0003***	0.0001	-0.0003***	0.00003
	(0.004)	(0.014)	(0.0003)	(0.010)	(0.00007)	(0.0007)	(0.00004)	(0.00003)
Fir Engraver	0.096***	0.063*	0.038***	0.032***	0.013***	0.017***	0.010***	0.008***
	(0.027)	(0.036)	(0.005)	(0.010)	(0.003)	(0.003)	(0.001)	(0.001)
Fir Engraver Squared	-0.007***	-0.006	-0.001***	-0.002**	-0.0003**	-0.0004***	-0.0002***	-0.0001***
	(0.002)	(0.004)	(0.0004)	(0.0007)	(0.0001)	(0.0001)	(0.00003)	(0.00002)
Pacific madrone Decline	0.055***	-0.001	0.049***	0.017***	0.008***	0.002	0.005***	-0.003***
	(0.018)	(0.030)	(0.005)	(0.001)	(0.001)	(0.002)	(0.0001)	(0.0009)
Pacific madrone Decline Squared	-0.004	0.002	-0.003***	-0.001**	-0.0001***	-0.0002	-0.0001***	0.00002
	(0.002)	(0.005)	(0.0005)	(0.001)	(0.00004)	(0.0002)	(0.00002)	(0.00001)
Other Blight	-0.023*	-0.003	-0.008***	0.002	-0.005***	0.001	-0.003***	0.0001
	(0.012)	(0.013)	(0.002)	(0.003)	(0.0006)	(0.0006)	(0.0003)	(0.0003)
Other Blight Squared	0.001	0.0003	0.0001	-0.00002	0.00002***	-0.00002	0.00001***	-0.000004
	(0.001)	(0.001)	(0.00007)	(0.00006)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	170,141	100,231	170,141	100,231	170,141	100,231	170,141	100,231
Adjusted R^2	0.473	0.883	0.476	0.884	0.478	0.884	0.481	0.884
Year × Census Block FE	Yes	No	Yes	No	Yes	No	Yes	No
Property and Year FE	No	Yes	No	Yes	No	Yes	No	Yes

Note: *p<0.1** p<0.05***p<0.01
All variables presented in tens of acres
All other covariates take on similar coefficients as in Table 1 and are omitted here for clarity

General housing and environmental coefficients take on expected values in all models. The number of acres significantly increases the value of a home, while the number of bedrooms is significant and negative in all models and square feet of the home is positive and significant. Although somewhat counterintuitive, bedrooms are found to be a negative quality in many other studies (Sirmans et al.2005). Since floor area is already controlled for, this may suggest more bedrooms indicate smaller bedrooms or lead to a lack of more desirable qualities not included in this study such as kitchen and living space. The significant negative coefficient estimate on house age shows that people generally prefer newer homes while the quadratic form of house age takes on a positive sign indicating that there is a turning point, most likely indicative of remodeled or refurbished historical properties. In all models, in-state buyers are estimated to pay around 8% less than out-of-state buyers. This phenomenon could be a result of less information available to the out of state consumers and is consistent with other real estate research (Heintzelman and Tuttle 2011). Having a view is estimated to have an unsurprisingly positive quality.

Forested acres are defined as coniferous, deciduous or mixed cover by the NLCD and are significantly positive within all buffer sizes. Some studies find particular forest types of vegetation to have negative impacts, especially if they obstruct views and encroach on useful or open land (Seong-Hoon, 2008), while many find positive impacts (Netusil, 2010; Mansfield et al. 2005 and Thompson et al. 1999). Several explanations for these particular positive findings are possible. Because other land cover types such as development and wetlands are not individually estimated in the model, forest cover may serve as a proxy for the absence of those potentially undesirable qualities. It is also possible that, on average, homeowners in Washington State simply value forest cover more than in other regions given the state's environmental history and outdoor recreational habits. In the same way, results show that living within city limits negatively impacts price or somewhat counter-intuitive. I hypothesize that without observations in Seattle and the Bellevue, living just outside of city limits offer positive qualities such as recreation and views whilst still being near urban amenities.

4.5 Discussion and Conclusion

As a whole, results show that economic impacts of forest blight in western Washington are consistently non-linear. That is, people react differently to the first acre of forest damage than to the one-hundredth acre. There are a few possibilities for this relationship. Past blight studies have shown that forest defoliation can in fact have positive effects on real estate (Holmes et al. 2010, Hansen and Naughton 2013) as well as negative impacts (Thompson et al. 1999, Holmes et al. 2006, Price et al. 2010) while natural view and open space literature also supports the hypothesis that thinner tree cover and clear views can have mixed impacts on property values depending on the region (See Benson et al. 1998, Patterson and Bolye 2002, Sander and Polasky 2009, Cavailhès et al. 2009 and Baranzini and Schaerer 2011). It is likely that average to moderate amount of aggregate blight offer a natural thinning process, opening views of the surrounding landscape, which, in western Washington, can include dramatic mountain ranges, water, or more forest. Due to natural composting, other advantages may include activities like recreational mushroom collecting. Another hypothesis for explaining positive effects, particularly those captured in the 0.5km and 1km ranges, is that home owners remedy visually damaged stands close to their home before a sale, leaving open space in place of blight that was recorded just months prior.

This thinning process can be natural and may add value until the undesirable aesthetics of dead and defoliated trees become an eyesore and outweigh any enhancements they initially offer. The tipping point between positive and negative impacts may be a result of intermittent blight activity becoming a large majority of the view shed itself. This hypothesis is consistent with the findings in this paper that people react to defoliation differently at different spatial ranges from their home. Derived from the pooled model and displayed in Table 10, the partial effects of aggregate blighted acres in respect to sale price, even two standard deviations away from the sample mean, are positive when observed 0.5 km from the home. Conversely, the same analysis, extended to the 1km model, reports a -11% impact on price. This asymmetry suggests that blight is tolerated as long as it is not obvious, or serves as a mechanism for improved views. However, larger areas of blight well beyond the parcel may lose its ability to improve views and become an undesired feature of the view itself. Beyond aesthetics, widely spread blight may serve as a proxy for wildfire probability, causing homebuyers to internalize fire risk into their purchase (Loomis, 2004).

Table 10 Estimated Elasticities of Aggregate Blight with Respect to Sale Price

	Pooled				Repeat Sales			
	Mean	1 Std. Dev.	2 Std. Dev.	3 Std. Dev.	Mean	1 Std. Dev.	2 Std. Dev.	3 Std. Dev.
Aggregate Blight 5km	0.02	0.00	-0.01	-0.03	0.01	0.01	0.01	0.01
Aggregate Blight 3km	0.02	0.01	-0.01	-0.02	0.01	0.00	-0.01	-0.01
Aggregate Blight 1km	0.19	0.05	-0.10	-0.25	0.08	0.02	0.00	0.00
Aggregate Blight 0.5km	0.53	0.35	0.16	-0.04	0.12	0.03	-0.01	-0.01

Note: All elesticities significant at the 10% level or better except the 0.5 km repeat sales model

When broken up into categories, the impacts of individual blighting agents become somewhat mixed in sign and significance (see Table 9). In pooled models, the consistency of the Douglas fir Beetle and Fir Engraver impacts with the aggregate blight model estimates are not surprising. Douglas fir Beetle damage occurs across more acres than any other agent in the dataset while the Fir Engraver also effects relatively large acreages, especially within the 3 and 5km buffers (see Table7). Consequently, it is likely that these two categories, along with similar impacts from Pacific madrone decline, drive the results of aggregate models discussed above. The “other” category, however, shows the opposite result. Where all other specifications yield diminishing, positive effects or inconsistent results, blighting agents contained in the “other” category demonstrate negatively significant linear impacts within 0.5 and 1km from a sale and diminishing negative effects within 3 and 5km buffers. As it stands, it may be difficult to know precisely how one or more of the 22 blight types making up the “other” category are driving these effects, one reasonable explanation is that many of the defoliators affect ornamental trees such as the Norway and Scotch pine, as well as hemlock and poplar used for landscaping. Thus, by damaging more coveted aesthetics close to the home, this collection of species yield immediate negative effects. These findings support literature that finds urban forest greenness to be a valuable societal attribute (Mansfield, 2005).

Aggregate repeat sales model magnitudes, both positive and negative, are much smaller than their pooled counterparts (see Table 8). This is expected as stricter spatial controls, meant to suppress price variation associated with omitted variables and spatial correlation, may also suppress real impacts in the process (Holmes et al. 2010). Mixed significance may, in part, be a product of a restricted dataset, especially when treatments are reduced to just a few hundred in smaller buffers. Further, outbreaks may contain several different blighting agents at once. Mixed significance of such similar and closely occurring events is also suggestive of some level of multicollinearity.

I run models searching for impacts of blight within 0.1 km of a parcel centroid. These models, not presented here, represented such a small area around a parcel that less than 100 total acres of blight was captured and yielded highly insignificant results. I also performed all regression using block group fixed effects and find that their results are highly consistent with block models. Given the success of the more restrictive block model, block group models are withheld from this study for simplicity.

Ultimately, results indicate that homeowner stand to benefit from keeping blight occurrences from reaching epidemic proportions. Furthermore, significant 3km and 5km model results suggest that forest health is a public good, and therefore should ellicit some level of public funding for management. From a policy standpoint, at first glance, the non-linear impacts presented here advocate for the mitigation of large, widespread outbreaks and to relax management measures where blight levels are considered low or natural. However, while a small areas of blight may go unnoticed by a homeowner or even desired at the time of viewing, its propensity to grow to epidemic proportions may be beyond the homeowner’s knowledge. Therefore, results may highlight a disparity between the risk that is perceived by a homeowner and the actual risk the homeowner is subjected to. If the latter is true, there is support for regional public policy regarding proactive thinning and spraying measures as well as informational campaigns to educate the public about forest pathogen risk.

Spittlehouse and Stewart (2003) emphasize the need for adaptive forest management including techniques that maintain tree species diversity and thinning forest in the face of insect disturbances and climate change. Descriptive data from the past three decades show a clear increase in pathogenic activity in Washington state (Dozic et al. 2012), while the work of Bentz et al. (2010) suggest that this trend will continue in response to climatic change. Since the problem is not static, there is a necessity for regional forest monitoring, forecasting, planning and strategies in response to climate change, in addition to current management (Sturrock et al. 2011).

While this paper expands the current knowledge of forest pathogen externalities in the region, future research should be explored to fully support the management suggestions above. For example, similar to Kovaks et al (2011), research should compare the economic impacts of future damages and the cost of current and future mitigation measures. More complex interactions within the landscape need to be explored, such as social perceptions of forest blight as they pertain to wildfire risk (Hansen and Naughton 2013; Loomis, 2010; Loomis, 2004). Future research should take advantage of increases in data availability, GIS functionality and computational advancements to expand similar research to state and other regional arenas.

CHAPTER 5
POLICY, PROBLEMS AND FURTHER WORK

5.1 Policy

The intent of this paper is to inform and support forestry policy. By using a non-linear model framework, the study proposes that the impacts of blight follow similar impacts exhibited by air and water pollution (Pindyck, 2007); in other words, their effects compound over time. In practice, these results suggest that proactivity is paramount for protection against economic forest health issues before they become catastrophic. Supporting policies would include cost sharing and new public forest protection funds.

Cost sharing is a mechanism that partially funds private parties to mitigate forest health problems. In Washington, the Department of Natural Resources will match up to 50% of treatment and tree removal cost given a set of criteria (WA Department of Natural Resources, 2015). Currently, private forest owners in Eastern Washington who control between 20 and 5000 acres are eligible for the program. Western Washington forest owners currently cannot receive the same state level funding; however, they can receive advice from Washington DNR on management and how to apply for federal funds.

While cost sharing encourages management on private property, this paper also demonstrates the need for management beyond what is privately owned. At the time of this papers writing, the Agricultural Act of 2014 (Public Law No: 113-79) otherwise known as “The Farm Bill” had just been passed. In addition to $1.2 billion in cost sharing measures, section

8204 of the bill expects to spend $25 million a year to help treat 45.6 million acres of insect damaged public forests in 35 states, including Washington. Section 8206 of the bill, the good neighbor agreement, incentivizes watershed restoration which by definition includes insect damage mitigation on public land.

Since paying a price that is disproportional to risk may lead to capital misallocation, this research offers other policy support within the field of asset pricing and consumer disclosure. Although I find evidence that consumer behavior does depend on forest health, results may still understate the true impacts for several reasons. Known as information bias (Kask and Maani, 1992), if a home buyer is not aware that blight is present, or that it has the propensity to grow, they are not able to capitalize impacts accordingly. Similarly, transformation bias can occur when consumers know about the problem, but fail to incorporate the full risk into their behavior (Kask and Maani, 1992). Further, knowledge of forest health and its impacts may be asymmetrically distributed between in-state and out-of-state buyers. In the same way that inspections disclose hidden structural issues with a home before it is sold, agents could disclose readily available insect and disease risk maps (Krist F.J. et al., 2014) to consumers to overcome information bias. Likewise, general public education about the nature of forest health risks could help avoid transformation bias in the future.

5.2 Problems

A caveat to this work comes from the accuracy, consistency and resolution of aerial surveys. As mentioned in this paper, survey accuracy is estimated to vary within ¼ mile and estimation techniques have changed over the time in which this data was collected. Given the scale, accuracy is less of an issue in 3 and 5 km models, but it is hard to confidently assume blight accurately falls within the boundaries of smaller 1km and 0.5 km models. Consequently, it is no surprise that models, capturing blight within 0.1 km from a sale, are all insignificant and dropped from this paper.

Due to a lack of housing data, my study is not able to incorporate major urban areas. Had I done so, result may have varied in several ways. As I mentioned above, the 0.1km model was estimated but yielded insignificant results, likely from very few treatments or poor spatial resolution. However, since urban forests tend to be located much closer to a property, using more urban observations may yield significant results in models searching for impacts closer to a parcel. When blight is categorized into respective agents, the “other” category yields immediate, negative linear results. Given that some blighting agents in the “other” category affect deciduous and ornamental trees, I suspect that more urban forest observations would cause the category to become more statistically significant and perhaps even larger in magnitude. Since the fir engraver and Douglas fir beetle effects are most likely derived from more rural observations, I would expect them to remain relatively unaffected.

Also not present in this paper, are results from interacting blighted area with total forest area. The reasoning behind the interaction is to test whether or not the positive impacts of forest cover depends on blight. Results show that the interaction between forest and blight was in fact negative and significant, suggesting that blight diminishes positive forest effects. Similarly, I test the effects of blighted area as a percentage of forest cover and find significantly negative impacts when forest cover is largely inundated by blight. Unfortunately, the two data sets, blight surveys and forest cover, are not always physically consistent with one another. Inconsistencies sometimes result in a buffer containing more blighted acres than forest, or blight situated in a location other than the forest cover. Therefore, to maintain data integrity, I ultimately keep forest cover as a control variable, include blight area separately, and highlight these ancillary exercises here for discussion purposes.

5.3 Further Work

Despite the usefulness of GIS in this study as it exists today, its rapid development marks a field that will offer new data for years to come. Recent examples of the evolutionary use of GIS in hedonic models include view shed analysis (Walls et al. 2015) and non-linear wetland identification (Mahan et al. 2000). Further, remotely sensed data, an input into many GIS applications, has the potential to give more precise measurements of blight, among many other natural and human processes. Remotely sensed data can be restricted in resolution, especially imagery derived decades ago. However, as imagery from space born sensors improve over time, studies, such as this, should leverage more precise remotely sensed data for primary or ancillary use.

Beyond data expansion and precision, work should also focus on more specific temporal and spatial scenarios. Examining impacts across a large scale allows this study to offer policy support on a regional level, however, local and city governments might benefit from more isolated studies. In such a way, local government could supplement state policy with more aggressive programs if their citizens are found to be more sensitive to blight and willing to pay more for protection. Studying the impacts of forest health across different temporal groups might also reveal useful interpretations. While this paper suggest that blight has economic implications, it assumes that impacts only vary with blight size. Temporal studies might reveal that, beyond size, impacts themselves change with time.

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Appendix

Geocoding Error Calculation

$$Pop\ Error > 40 \ = \frac{\alpha+\varepsilon+\gamma+\delta}{n_{41}} \tag{4}$$

$$Pop\ Error > 50 \ = \frac{\varepsilon+\gamma+\delta}{n_{51}} \tag{5}$$

Where n_{41} and n_{51} represent the population size above a given sensitivity range and α, ε , γ and δ are total errors estimated in each respective range 41-50, 51-60, 61-75, 76-90.

$$\alpha = \frac{error_{41\to50}}{100} \times n_{41\to50} \tag{6}$$

$$\varepsilon = \frac{error_{51\to60}}{100} \times n_{51\to60} \tag{7}$$

Variable Names

Variable in Table	Variable in dataset	Variable in R*
Property Characteristics	*Property Characteristics*	*Property Characteristics*
Sale Price (Dollars)	Index_Sales	Index_Sales
Acres	ACRES	ACRES
View	View	View
Local Buyer	LOCAL_BUY	LOCAL_BUY
House Age (Years)	HOUSE_AGE	HOUSE_AGE10
Floor Area (Square feet.)	SqrFeet	SqrFeet100
Bedrooms	Bedrooms	Bedrooms
City	City	City
3km Forest Cover (Acres)	3km_Cover	X3km_Cover10
1km Forest Cover (Acres)	1km_Cover	X1km_Cover10
0.5km Forest Cover (Acres)	.5km_Cover	X.5km_Cover10
Treatment Variables	*Treatment Variables*	*Treatment Variables*
5km All Blight	5km_Blight	X5km_Blight10
3km All Blight	3km_Blight	X3km_Blight10

1km All Blight	1km_Blight	X1km_Blight10
.5km All Blight	.5km_Blight	X.5km_Blight10
5k Douglas-fir beetle	5k Douglas-fir beetle	X5k.Douglas.fir.beetle10
5k Fir engraver	5k Fir engraver	X5k.Fir.engraver10
5k Pacific madrone decline	5k Pacific madrone decline	X5k.Pacific.madrone.decline10
5k Other	5k Other	X5k.Other10
3k Douglas-fir beetle	3k Douglas-fir beetle	X3k.Douglas.fir.beetle10
3k Fir engraver	3k Fir engraver	X3k.Fir.engraver10
3k Pacific madrone decline	3k Pacific madrone decline	X3k.Pacific.madrone.decline10
3k Other	3k Other	X3k.Other10
1k Douglas-fir beetle	1k Douglas-fir beetle	X1k.Douglas.fir.beetle10
1k Fir engraver	1k Fir engraver	X1k.Fir.engraver10
1k Pacific madrone decline	1k Pacific madrone decline	X1k.Pacific.madrone.decline10
1k Other	1k Other	X1k.Other10
0.5k Douglas-fir beetle	.5k Douglas-fir beetle	X.5k.Douglas.fir.beetle10
0.5k Fir engraver	.5k Fir engraver	X.5k.Fir.engraver10
0.5k Pacific madrone decline	.5k Pacific madrone decline	X.5k.Pacific.madrone.decline10
0.5k Other	.5k Other	X.5k.Other10
Census Block FE	BLOCK	BLOCKf
Year	y	yf
-	Repeat	Repeatf

*Note that R Variable may have been transformed

R code

Load Data

```
Rdata8 <- read.csv("C:/Users/BlairLo/Desktop/REM Year 2/Thesis Progress/thesis/Rdata8.csv")
```

Load Packages

```
library("lfe", lib.loc="C:/Program Files/R/R-3.1.3/library")

library("stargazer", lib.loc="C:/Program Files/R/R-3.1.3/library")

library("knitr", lib.loc="C:/Program Files/R/R-3.1.3/library")
library("rmarkdown", lib.loc="C:/Program Files/R/R-3.1.3/library")
library("lmtest", lib.loc="C:/Program Files/R/R-3.1.3/library")

library("sandwich", lib.loc="C:/Program Files/R/R-3.1.3/library")
```

Transform Aggregate Blight Variables by 10

```
Rdata8$X5km_Blight10<-(Rdata8$X5km_Blight/10)
Rdata8$X3km_Blight10<-(Rdata8$X3km_Blight/10)
Rdata8$X1km_Blight10<-(Rdata8$X1km_Blight/10)
Rdata8$X.5km_Blight10<-(Rdata8$X.5km_Blight/10)
```

Transform Blight Category Variables by 10

```
Rdata8$X.5k.Douglas.fir.beetle10<-(Rdata8$X.5k.Douglas.fir.beetle/10)
Rdata8$X1k.Douglas.fir.beetle10<-(Rdata8$X1k.Douglas.fir.beetle/10)
Rdata8$X3k.Douglas.fir.beetle10<-(Rdata8$X3k.Douglas.fir.beetle/10)
Rdata8$X5k.Douglas.fir.beetle10<-(Rdata8$X5k.Douglas.fir.beetle/10)
Rdata8$X.5k.Fir.engraver10<-(Rdata8$X.5k.Fir.engraver/10)
Rdata8$X1k.Fir.engraver10<-(Rdata8$X1k.Fir.engraver/10)
Rdata8$X3k.Fir.engraver10<-(Rdata8$X3k.Fir.engraver/10)
Rdata8$X5k.Fir.engraver10<-(Rdata8$X5k.Fir.engraver/10)
Rdata8$X.5k.Pacific.madrone.decline10<-(Rdata8$X.5k.Pacific.madrone.decline/10)
Rdata8$x.1k.Pacific.madrone.decline10<-(Rdata8$X1k.Pacific.madrone.decline/10)
Rdata8$X1k.Pacific.madrone.decline10<-(Rdata8$X1k.Pacific.madrone.decline/10)
Rdata8$X3k.Pacific.madrone.decline10<-(Rdata8$X3k.Pacific.madrone.decline/10)
Rdata8$X5k.Pacific.madrone.decline10<-(Rdata8$X5k.Pacific.madrone.decline/10)
Rdata8$X.5k.Other10<-(Rdata8$X.5k.Other/10)
Rdata8$X1k.Other10<-(Rdata8$X1k.Other/10)
Rdata8$X3k.Other10<-(Rdata8$X3k.Other/10)
Rdata8$X5k.Other10<-(Rdata8$X5k.Other/10)
```

Other variable transformations

```
Rdata8$HOUSE_AGE10<-(Rdata8$HOUSE_AGE/10)
Rdata8$SqrFeet100<-(Rdata8$SqrFeet/100)
Rdata8$X.5km_Cover10<-(Rdata8$X.5km_Cover/10)
Rdata8$X1km_Cover10<-(Rdata8$X1km_Cover/10)
Rdata8$X3km_Cover10<-(Rdata8$X3km_Cover/10)
Rdata8$BLOCKf<-factor(Rdata8$BLOCK)
Rdata8$yf<-factor(Rdata8$y)
Rdata8$Repeatf<-factor(Rdata8$Repeat)
```

Fixed effects linear models - aggregate blight models

```
x.5k_quad<-felm(log(Index_Sales)~X.5km_Blight10+I(X.5km_Blight10^2)+ACRES+View+LOCAL_B
UY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X.5km_Cover10|BLOCKf*
yf,data=Rdata8,clustervar="BLOCKf")
```

```
x1k_quad<-felm(log(Index_Sales)~X1km_Blight10+I(X1km_Blight10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X1km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x3k_quad<-felm(log(Index_Sales)~X3km_Blight10+I(X3km_Blight10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X3km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x5k_quad<-felm(log(Index_Sales)~X5km_Blight10+I(X5km_Blight10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X3km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x.5k_quad_rep<-felm(log(Index_Sales)~X.5km_Blight10+I(X.5km_Blight10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x1k_quad_rep<-felm(log(Index_Sales)~X1km_Blight10+I(X1km_Blight10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x3k_quad_rep<-felm(log(Index_Sales)~X3km_Blight10+I(X3km_Blight10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x5k_quad_rep<-felm(log(Index_Sales)~X5km_Blight10+I(X5km_Blight10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")
```

Fixed effects linear models - blight categories

```
x.5k_quad_cat<-felm(log(Index_Sales)~X.5k.Douglas.fir.beetle10+I(X.5k.Douglas.fir.beetle10^2)+X.5k.Fir.engraver10+I(X.5k.Fir.engraver10^2)+X.5k.Pacific.madrone.decline10+I(X.5k.Pacific.madrone.decline10^2)+X.5k.Other10+I(X.5k.Other10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X.5km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x1k_quad_cat<-felm(log(Index_Sales)~X1k.Douglas.fir.beetle10+I(X1k.Douglas.fir.beetle10^2)+X1k.Fir.engraver10+I(X1k.Fir.engraver10^2)+X1k.Pacific.madrone.decline10+I(X1k.Pacific.madrone.decline10^2)+X1k.Other10+I(X1k.Other10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X1km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x3k_quad_cat<-felm(log(Index_Sales)~X3k.Douglas.fir.beetle10+I(X3k.Douglas.fir.beetle10^2)+X3k.Fir.engraver10+I(X3k.Fir.engraver10^2)+X3k.Pacific.madrone.decline10+I(X3k.Pacific.madrone.decline10^2)+X3k.Other10+I(X3k.Other10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X3km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")

x5k_quad_cat<-felm(log(Index_Sales)~X5k.Douglas.fir.beetle10+I(X5k.Douglas.fir.beetle10^2)+X5k.Fir.engraver10+I(X5k.Fir.engraver10^2)+X5k.Pacific.madrone.decline10+I(X5k.Pacific.madrone.decline10^2)+X5k.Other10+I(X5k.Other10^2)+ACRES+View+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)+SqrFeet100+Bedrooms+City+X3km_Cover10|BLOCKf*yf,data=Rdata8,clustervar="BLOCKf")
```

```
x.5k_rep_cat<-felm(log(Index_Sales)~X.5k.Douglas.fir.beetle10+I(X.5k.Douglas.fir.beetle10^2)+X.5k.Fir.engraver10+I(X.5k.Fir.engraver10^2)+X.5k.Pacific.madrone.decline10+I(X.5k.Pacific.madrone.decline10^2)+X.5k.Other10+I(X.5k.Other10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x1k_rep_cat<-felm(log(Index_Sales)~X1k.Douglas.fir.beetle10+I(X1k.Douglas.fir.beetle10^2)+X1k.Fir.engraver10+I(X1k.Fir.engraver10^2)+X1k.Pacific.madrone.decline10+I(X1k.Pacific.madrone.decline10^2)+X1k.Other10+I(X1k.Other10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x3k_rep_cat<-felm(log(Index_Sales)~X3k.Douglas.fir.beetle10+I(X3k.Douglas.fir.beetle10^2)+X3k.Fir.engraver10+I(X3k.Fir.engraver10^2)+X3k.Pacific.madrone.decline10+I(X3k.Pacific.madrone.decline10^2)+X3k.Other10+I(X3k.Other10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")

x5k_rep_cat<-felm(log(Index_Sales)~X5k.Douglas.fir.beetle10+I(X5k.Douglas.fir.beetle10^2)+X5k.Fir.engraver10+I(X5k.Fir.engraver10^2)+X5k.Pacific.madrone.decline10+I(X5k.Pacific.madrone.decline10^2)+X5k.Other10+I(X5k.Other10^2)+LOCAL_BUY+HOUSE_AGE10+I(HOUSE_AGE10^2)|Repeatf+yf,data=Rdata8,clustervar="Repeatf")
```

Table Generation

```
stargazer(coeftest(x.5k_quad),coeftest(x.5k_quad_rep),coeftest(x1k_quad),coeftest(x1k_quad_rep),coeftest(x3k_quad),coeftest(x3k_quad_rep),coeftest(x5k_quad),coeftest(x5k_quad_rep),type="html",font.size="small",no.space=TRUE,out="C:\\Users\\BlairLo\\Desktop\\REM Year 2\\Thesis Progress\\thesis\\testgrapgic20")

stargazer(coeftest(x.5k_quad_cat),coeftest(x.5k_rep_cat),coeftest(x3k_quad_cat),coeftest(x3k_rep_cat),coeftest(x1k_quad_cat),coeftest(x1k_rep_cat),coeftest(x5k_quad_cat),coeftest(x5k_rep_cat),type="html",font.size="small",no.space=TRUE,out="C:\\Users\\BlairLo\\Desktop\\REM Year 2\\Thesis Progress\\thesis\\testgrapgic21")
```