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The Economic Impacts of Forest Timber Methods in Washington State: a Hedonic Approach

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THE ECONOMIC IMPACTS OF FOREST TIMBER METHODS

IN WASHINGTON STATE: A HEDONIC APPROACH

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by

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ABSTRACT

THE ECONOMIC IMPACTS OF FOREST TIMBER METHODS

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Washington State is one of the nation's leaders in timber production. This paper establishes literature gap regarding the economic impacts of forest timber management methods. In this research, I employ a data set of 170,141 home sales across eleven counties of western Washington to estimate the impact that even-age and uneven-age forest cutting methods have on the local real-estate market. I estimate two sets of hedonic fixed effect regression models to control for omitted variable bias and spatial autocorrelation. The results show statistically significant impacts on property values for both cutting methods, adding important information for forest managers.

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I INTRODUCTION

Washington State is among the top producers of timber in the nation. As a state, Washington is the fifth largest state for timber employment and timber job wages (U.S. Bureau of Labor Statistics 2014). Washington State produced just over 3.2 million board feet of timber in 2014 and of its 39 counties, 32 of them are involved in the timber industry (WSDNR 2015). As a leader in the timber industry in the nation, the amount of forests cuts and forest activity across the state is evident. Using the latest data available, there have been over 100,000 permitted active forestry activities since 1995 (WSDNR 2016).

The permitted forest practices is monitored by the Washington State Department of Natural Resources (WSDNR). The WSDNR details all the operations and methods employed to harvest the selected forest. Forest managers have many considerations and tools to choose from, and among those choices are what methods are used to fell the forest (Florence 1977). There are two styles of harvesting that can be done, even-age and uneven-age methods. The major differences between these two operations is the post-harvest effect (Bliss 2000). even-age methods involve harvesting the entirety of a tree stand leaving only stumps post-harvest (Nyland 2016). Uneven-age methods are more selective; these methods involve picking specific trees to cut and leaving the unwanted trees standing (Nyland 2016). The most controversial method of even-age methods is clear-cutting (Boughton 1990). Clear-cutting for timber poses an assortment of personal benefits and social challenges to a forester.

The practice of clear-cutting or clear-felling has a long history. The use of clear-cutting in Europe alone is centuries old (Keenan and Kimmins 1993). The method of clear-cutting is the most economically cost-effective method of forest harvesting (Smith 1972). Clear-cuts are followed by large environmental impacts as well as major scrutiny and public animosity than other cutting methods. People see these operations as leaving scars on the landscape and causing major environmental harm (Keenan and Kimmins 1993; Ribe and Matterson 2002). Across the United States, there is a largely negative view of clear-cuts (Bliss 2000). Multiple surveys and ethnographic studies have shown that people from the Pacific Northwest to the southern United States have a negative perception of the practice (Bliss 2000). Forest managers are caught between a decision paradigm of using a method that is the most efficient harvesting method, but has substantial negative public support. The economic research to aid a forest manager in choosing the most socially optimal method is severely lacking. For optimal forestry management choices, the full economic costs of even-age and uneven-age methods need to be evaluated.

The purpose of this research is to estimate the economic impact of even-age and uneven-age forest management methods used in western Washington's forests. There exists a major literature gap on the economic impact of forest management practices in general, and none exist that evaluate the impact of even-age and uneven-age methods. This thesis uses the real estate market in western Washington to estimate the consumer willingness to pay (WTP) towards the different forest practices used across the forests of western Washington. Combining the capabilities of geographic information systems

(GIS) with the estimation ability of ordinary least squares regression and the hedonic price method, the impacts of even and uneven-age methods across time and distance is evaluated.

The second chapter discusses what is involved in the even and uneven-age operations, the prior perception research of clear-cuts, and how economics has studied forests and other externality problems. Chapter 3 focuses on the data sets used in this paper, use of geographic information systems, and the study area. Chapter 4 is the journal article that contains its own introduction and condensed literature review, describes the empirical methods, issues during the research and results discussion. Chapter 5 concludes the thesis with policy implications, research problems, and future research suggestions.

II LITERATURE REVIEW

In this section, I discuss a wide variety of topics regarding economics, forests and forest management. This research focuses on evaluating the economic impact that the varying forest management styles employed by foresters have on the surrounding real-estate markets. The literature review discusses what even-age and uneven-age forest practices entail, public perception studies of even-age methods, the theoretical and empirical research regarding natural resource economics of forests, and how this research fills in a major literature gap.

2.1 Methods of Cutting

There are traditionally two classifications for cutting forests., even-aged and uneven-aged (Boughton 1990). These two groups are further divided into five different types: clear-cut, seed tree, shelterwood, single tree selection, and group selection (Boughton 1990).

2.1.1 Even-aged

These methods are used to create tree stands that consist of same species of trees with all similar age (Nyland 2016).The most controversial method is clear-cutting, which is politically ,ecologically , and publicly troublesome (Nyland 2016). Clear-cutting involves harvesting all the standing trees in the designated area in one operation (Boughton 1990). These methods come with many ecological concerns including soil erosion, increased fire hazard due to increased logging operations remains, and loss of habitat to wildlife in forest (Nyland 2016). The next even-aged method is seed tree. This approach involves cutting away all the trees, except for the desired mature trees so they can leave seeds to produce a new stand (Nyland 2016). This practice involves a large amount of site preparation to ensure that competing shrubs and trees do not inhibit or harm the growth of the desired seedlings (Nyland 2016). The last even-aged method is shelterwood. This method is an alteration of the seed tree approach. Shelterwood cuts leave enough mature trees to create seedlings, as well as create enough shade to protect the seedlings (Nyland 2016). Certain species of trees require standing trees to create shade to survive and grow into mature trees (Nyland 2016). Once the new seedlings become mature enough, the mature trees that were left before are harvested (Nyland 2016). Shelterwood cuts are viewed as the most favorable of all even-age methods by environmentalist groups because they do not totally strip a hillside or area of all its trees as clear-cuts do (Nyland 2016).

2.1.2 Uneven-aged

The first of two methods for uneven-aged forest practices is single tree selection. Single tree involves cutting trees that are close to the end of life and are the healthiest and highest quality the particular tree can be and harvesting them (Nyland 2016). This method involves going through a tree stand and attempting to cut trees at their peak, before decay or diseases sets in (Nyland 2016). This approach requires a large amount of management and monitoring before harvest, and levels of harvest can be controlled to create sustainable yields (Nyland 2016).The second method, group selection, involves cutting small groups of trees from a stand in order to stimulate the surrounding forest to start regenerating (Lamson and Leak 2000). This method mimics the same kind of effect small scale disturbances have on a forest (Lamson and Leak 2000). Using the group method, there can be a regular harvest of the forest that can be completed over a long period of time (Lamson and Leak 2000).

2.2 Clear-Cut Perceptions Studies

Following the passage of the many forestry and environmental protection acts, foresters and academics were met with a new question. Why does the public dislike and even forbid the use of clear-cutting? Ribe and Matteson (2002) in their perception research surveyed people in different ideological groups in western Washington and Oregon about their views of different forestry methods and their impact on the forest ecosystem. The researchers found that the people surveyed fell into three different groups: those who valued the forest for the products they can gain from it, environmental protectionists, and people who shared both group's values (Ribe and Matterson 2002). Of these groups, only the people who valued a forest for what can be produced with it were in favor of clear-cutting practices. The outcome of the study showed that new forest practices in the United States could make clear-cutting and other old forestry practice outdated or even outlawed (Ribe and Matterson 2002).

Prior literature has described the varying reasons as to why the public has oppositions to clear-cuts. The first most documented reason was aesthetics of scenery (Palmer et al. 2005, Ribe and Matteson 2002; Bliss 2000). People do not like the sight of clear-cuts at all levels and as intensity increase so does peoples' dislike (Palmer et al. 2005). Other prevalent reasons are environmental and ecological concerns (Ribe and Matterson 2002; Bourke and Luloff 1994). When Ribe and Matterson (2002) educated people about clear-cut usage and how it can be beneficial, people still insisted on restrictions for environmental impacts. Their study also showed that people classify clear-cuts as a part of "old forestry" and see it as the most unpopular part of forestry in today’s society (Ribe and Matterson 2002). The public's perception of clear-cuts and other forest management techniques has caused foresters to judge a plan's feasibility heavily based upon the public opinion of the aesthetics of the outcome (Ribe and Matterson 2002; Greider and Garkovich 1994). Ribe (2002) argues there is potential for managers to incorrectly predict or choose inadequate management strategies if managers are fixated on public opinion. He demonstrates that there are chances for managers to use socially questionable techniques if the manager demonstrates to the concerned public why clear-cutting is required (Ribe 2002).

2.3 Natural Resource Economics and Forests

The earliest economic research into forests and forestry focused solely on modeling optimal tree harvests. All the models created in the early literature seek to solve and depict the optimal cutting age of a forest. The optimal age in all of these models is the outcome where “the marginal return of delaying harvest is equal to the forgone interest based on the value of the stand and the land" (Amacher, Ollikainen and Koskela 2009, pg. 11). There are two major models that stand out in forestry economics, the Faustman Rotation Model and the Hartman Model of Timber and Amenity Production. These two models do not quantify the benefit of forests from people’s uses of a forest like recreation or existence value; the models look to maximize a forest manager’s timber value (TV) of a particular stand. The Faustman and the Hartman models are focused on when a single type of even-aged tree stand should be harvested. Amenities that standing forests have like environmental, recreational and aesthetic benefits are only taken into account in the Hartman model and not the

Faustman model (Amacher, Ollikainen and Koskela 2009). Modeling optimal harvest for uneven-aged tree stands has occurred, but these problems are far more complex and only began being modeled in the 1970's. The now seminal papers of Adams and Ek (1974), Adams (1976) and Buoginoro and Michie (1980) were the first to study and model uneven-aged forest harvest.

The recent literature on optimal rotation incorporate benefits of a forest like carbon sequestration and other environmental amenities into the decision process. Diaz-Balteiro et al. (2014) specifically modeled the efficient cutting age that takes into account fire danger, carbon capture benefits and stand age. Other models have added the impact of biodiversity and conservation into the optimal rotation model, like Nghiem (2014). A recent model created by Tahvonen (2016) improves upon the other decision models with uneven-age cutting decisions as well as regeneration rates of the forests to decide optimal rotation age.

Much of forest economics today still uses similar models to describe many of the different forestry management regimes and problems that forest managers face. Among the many topics are catastrophic events like fire, storms, forests pests and diseases, and deforestation (Reed 1984, Englin et al. 2000, Haight et al. 1995, Anderson et al. 1987, Williams and Nautiyal 1992).

2.4 Empirical Natural Resource Economics and Forests

In contrast to the theoretical models and research regarding optimal harvesting choice of forest managers, the empirical natural resources economics work regarding forests evaluates the non-use value of forests. Non-use value also called non-timber value (NTV) is the measure or value that people place on a forest not for the amount of timber it could supply, but for other services (Mattsson and Li 1994, Pearce 1998). There exist multiple techniques in economics to estimate the NTV of forests, the three predominant methods that I discuss are Contingent Valuations (CV), Travel Cost Method (TCM), and Hedonic Pricing Method (HPM). Contingent Valuation is classified as a stated preference method and involves surveying consumers or users of a forest, like hikers and other recreationalists, what is their Willingness-to-Pay (WTP) for a particular good or service of the forest (Hanemann 1994). These methods have been applied to evaluate a wide variety of environmental benefits including wetlands, endangered species, and general recreation. (Ghermandi et al. 2008, Richardson and Loomis 2009, Rosenberger and Loomis 2000).

Travel Cost Method and the Hedonic Price Method differ from stated preference methods in that they do not explicitly ask the consumer what their WTP for a particular good or amenity is. Instead of asking for WTP estimates like in CV studies TCM and HPM are revealed preference methodologies and essentially let people's "wallets" speak for them. Researchers use people's spending patterns as a method to estimate a person's given WTP for an amenity. TCM, for example, uses surveys and asks the visitors a mix of socio-demographic questions and the visitors' points of origin. (Loomis and Eichhorn 2000). Using the visitors' locations gained from the surveys, researchers estimate the average cost of traveling to the site being valued, usually using an hourly wage gained from the survey. TCM methods primarily study open access public goods like forests and parks. This methodology has been applied to topics of tropical ecotourism, national parks, and outdoor recreation. (Menkhaus and Lober 1996, Bateman et al. 1996, and Fix, Loomis and Eichhorn 2000).

The Hedonic Price Method was first described in economics by Rosen (1974) in his now seminal paper. In the simplest terms, Rosen (1974) demonstrated that any good's value can be ascertained by its characteristics. For example, a home's sales price is representing all the particular characteristics that a property has, i.e. number of bedrooms, bathrooms, home square footage, and importantly a home location as well. The location of a property relative to the surroundings has impacts on the sale price. Homes in neighborhoods with better schools and close to public amenities like forests and parks are worth more in comparison to homes close to garbage-dumps and industrial areas.

In their meta-analysis of HPM home sale research, Sirmans et al. (2007) state that of all the characteristics of a home: square footage, lot size, age, bedrooms, bathrooms, garage, swimming pool, fireplace, and air conditioning have the most effect on a home's sales price. However, Sirmans et al. (2007) do argue that their relative strength and impact on a sales price varies with income, geographic location, and time. The use of HPM with home sales data to estimate a monetary value/impact of amenities or changes in the surroundings is common practice in economics today (Zietz, Zietz and Sirmans 2007). For example, for every 1/10 of a mile closer to a neighborhood park, a home was 1.3% more expensive than those in other neighborhoods in an HPM study by Leonard, Zhang, and Hoehner (2014). Another study showed apartment prices are negatively related to distance from green belts in the city (Herath, Choumert and Maier 2015). HPM is the same methodology used in this study and is discussed in greater detail in the subsequent methodology chapter.

This research looks at the non-timber values that people ascribe to the varying forest practices that forest managers can apply in their forests, but more specifically even-aged and uneven-aged methods. The literature on NTV of forests is vast and covers many topics. Prior Studies have focused on the NTV forests provide on topics such as biological diversity support, environmental protection, recreational use, aesthetic value, wildfire impacts and forest blights and pests (Pearce 1998). Below some of the research topics are discussed using a wide range of methods.

There is substantial literature that has evaluated the WTP of visitors and recreationists. Major services of forests that have been evaluated are the recreational and ecotourism values provided to society by their existence. Scarpa et al. 2000, used the CV method to evaluate the recreational benefits that the creation of Nature Reserves has on Irish recreationists. They estimated that the induction of more forests into the Irish nature reserves system has led to an increase of about 7.5 million pounds to the social benefit of Ireland (Scarpa et al. 2000). This increase in the social welfare shows that the NTV of the forests increased, meaning people value them more. Madureira et al. (2011), using CV methods, surveyed residents on their likelihood for paying to support a variety of forestry management styles in Portugal. They found that there is statistically significant evidence to show that taxes for conservation methods can be applied to preserve forests rather then cut the forest for cork.

Lindhjem and Mitani (2012) used the CV method to evaluate forest owner's willingness to accept payment to conserve their private forests rather then cut in Norway. They found an average willingness to accept payments of NOK 1800 per hectare of forest. They argue that the large costs can be avoided if smaller private forests and absentee forest owners were targeted by these polices first. Haghjou et al. (2016) used the CV method to evaluate the economic value of the Arasbaran Forests in Iran. They found that the survey respondent's demographics had major impacts on the WTP for conservation of the forests. They cite "respondents' level of education, income, number of annual visits to the forests, and their friendly attitudes towards the Arasbaran forests had significant positive impacts on willingness to pay" (Haghjou et al. 2016).

Prior literature heavily relies upon the TCM to evaluate the recreational and ecotourism WTP of forests. Dwyer et al. (1983), used TCM to evaluate the WTP of visitors to three forests in their study. Their WTP found was close to $10 (1983 dollars). Their full analysis of the differing WTP for the different forest in their study area are due to the varying amenities associated with each forest. Forests with higher WTP have more attractions, closer to user's home, and had less deterioration of the forest (Dwyer et al. 1983).

Englin and Mendelsohn (1991) evaluated people's preferences for different forest practices and amenities of the forested area. They found the willingness to travel for forests that had varying characteristics. Examples of the variation are trails with campsites, trails that had or went through clear-cuts, and trails with long dirt roads to gain access. Englin and Mendelsohn (1991) found that the average person in their study was willing to spend $2.61 for every extra mile of old-growth forest in the area they were traveling to. In a TCM study that evaluated the WTP for Costa Rica's tropical forests Menkhaus and Lober (1996), used the Monteverde Cloud Forest Biological Reserve as the study area and found large WTP for visitors. The study found an average per person evaluation of about USD $1150. They also were able to create an estimation of the value of the Monteverde Cloud Forest Biological Reserve (USD $4.5million) and a total value for the Costa Rican US tourists visiting all of Costa Rica's rainforest (USD $65 million) (Menkhaus and Lober 1996).

Robinson, Hite and Hanson (2016) used the TCM to evaluate the responses of 563 of visitors the Gulf Coast Region of the US. Their respondents were surveyed regarding the "beach improvements after the Deepwater Horizon Spill" (Robinson, Hite and Hanson 2016). They estimated the mean WTP for the existence of pre-Deepwater Horizon Spill beach quality was $29.18 per person. They also found that "visitors receive eight times more benefit from having future generational access to pre-DWH oil spill beach resource quality versus having the same quality without visiting." Bertram and Larondelle (2017) used the TCM to evaluate an urban forest in Berlin, Germany. Their results found a "consumer surplus of 14.95 € per visit" and that there are significant differences in demand elasticities when origin of visitor is taken into account.

Using the HPM, Tyrväinen, and Miettinen (2000) estimate the willingness to pay for an urban forest and its services provide to the people in Salo, Finland. Their findings showed on average people who lived one-kilometer closer in proximity to the local city forest had an increase of 5.9% to their home values. It can be interpreted that people are willing to pay higher home prices for living near an urban forest, signaling consumers' positive preference for the forest.

Research similar to Tyrväinen and Miettinen (2000) uses HPM, but attempts to evaluate the economic impact that exogenous events like wildfires, tree blight, and the construction of wind turbines have on the surrounding economy are analogous to the methods employed in this paper. Stetler, Venn, and Calkin (2010) combined GIS and HPM to approximate the impact that wildfires within 5, 10, and 15 kilometers of their home sales set had on their prices. The impacts estimated were significant for both distances. The homes within 5 km had a reduction of 21%, 10k lost 9.5% and 15k lost 3.5% of their original home value.

Using large data sets comprised of home sales, Thompson et al. (1999) and Price et al. (2010) estimated the impact of tree blight in Lake Tahoe Basin and Grant County Colorado, respectively. Both studies show similar findings of decreased housing values for having homes near dead trees due to blight. Thompson et al. (1999) showed that the median home sale price in their study lost around $26,000, a dramatic decline in home value. The findings of Price et al. (2010) were more precise than those of Thompson et al. (1999), in that they were able to prescribe values to the home price reduction on a per tree basis. They found that for every tree killed within the buffers of 100m home prices declined $648; within 0.5km homes lost $43 per tree, and $17 per tree within 1km (Price et al. 2010). Heintzelman and Tuttle (2012), using similar methods as the earlier mentioned HPM papers, evaluate the impacts that the construction of wind facilities has had on the surrounding communities. The findings of their research showed that home sales had an inverse relationship with proximity to the turbines, but the turbines' impact did decay the further the home sales were from the turbines. The impacts for homes close to the turbines were large, ranging 8% - 14% before decaying to a range of 2% - 8% (Heintzelman and Tuttle 2012).

Zygmunt and Gluszak (2015) used undeveloped land sales and the HPM model to estimate the impact of proximity to forests in Poland. Their results reflect what most forest proximity literature has found, positive impacts for proximity to forests. In their study, they found on average a “one-hundred-meter increase in distance from the forest decreases land value by 3%” (Zygmunt and Gluszak 2015). Using HPM Li, Xiaoshu, et al. (2016) evaluate the impact that the damage of the hemlock woolly adelgid forest pest to local forests has on the surrounding real-estate market. Using a standard fixed-effect hedonic model and a repeat sales model, they estimated the impacts of this forest pest. They found that damaged trees within 100m buffer of the home decreased home prices by 0.3% (Li, Xiaoshu, et al. 2016).

2.5 Evaluating Impact of Forest Management

The relevant literature regarding HPM and forest management schemes like clear cutting and selective cutting is severely lacking. Much of the research completed evaluates the impacts of simply having forests near properties. The consensus of these studies is that people value living near woodlands and forests (Powe et al. 1997; Garrod and Willis 1992; Tyrväinen and Miettinen 2000, Izon et al. 2010, Zygmunt and Gluszak

2015). As of writing this thesis, there are only three studies that have evaluated the impacts that forests and the timber harvesting schemes used within forests have. The relevant studies completed by Englin and Mendelsohn (1991), Mattsson and Li (1994), and Kim and Johnson (2002) evaluated the impact of these forest practices, each with different methods.

The earliest research that applies to this thesis work is the TCM study completed by Englin and Mendelsohn (1991). They collected overnight permits for four United State Forest Service (USFS) wilderness areas in Washington State and used these permits to estimate the WTP of the users of the camp sites. Englin and Mendelson (1991) then combined the permit data with census data and the USFS trail characteristic data for each wilderness area. While their study does not look solely at the impact of clear-cutting and other forest activities the data and results they produced show the earliest impacts that the presence of clear-cut activity had on the WTP. In similar fashion to the perception studies discussed earlier, they found negative impacts on the WTP for visitors to wilderness areas that contained trails that had clear-cut activity. Their exact estimates found the average camper would spend $0.58 per mile of trail to avoid the presence of a clear-cut visible from the trail (Englin and Mendelsohn 1991).

Mattsson and Li (1994) evaluated the WTP of Swiss forest management techniques. They used the CV method and were able to surveys 436 respondents. The goal of the study was to ascertain the WTP of the silviculture practice of replanting post clear-cut and gain the WTP for different forest tree make up. Comparable to the previous perception studies, Mattsson and Li (1994) found that people prefer tree stands that seem more "mature" and have a variety of tree species. A major takeaway is that the Swiss people preferred in all cases timber activity management that left a forest with trees meeting the perceptions of a mature and diverse forest (Mattsson and Li 1994). While the study pertains to Swiss forest preferences, the prior socioeconomic literature highlights similar responses by people in the United States.

The most similar work to this research has been done over small areas in Corvallis, Oregon. Kim and Johnson (2002) used the McDonald-Dunn Forest in Corvallis, Oregon and estimated the effects of multiple forest characteristics had on housing prices in the area. Kim and Johnson (2002) found that a house with a view of a clear-cut had a substantial price decrease, just over $16,000 (1995 dollars), per house on average (Kim and Johnson 2002). This is a substantial decrease in home prices and demonstrates the consumer preference that people do not support clear-cutting activity. It is a powerful empirical result that supports all of the perception studies conducted by the likes of Palmer et al. (2005), Ribe and Matteson (2002) and Bliss (2000). Kim and Johnson's monetary impacts size is not necessarily transferrable to western Washington, but the direction of the impact should be equivalent.

2.6 Literature Gap

A quick synopsis of the relevant literature previously discussed is presented below in Table 1. As mentioned before the major significance of this study is to fill in the major literature gap that exists in economics. The work of Englin and Mendelsohn (1991) and Mattsson and Li (1994) are important first works in economics that hint to the economic impact that people have towards specific forest timber practices. Their results only suggest the direction of the impact that forest timber activities have. Mattsson and Li (1994) is the only study that does not have an explicit value for the impact of clear-cutting, but they do note a decrease or negative relationship between clear-cutting and people's WTP.

Year	Study	Study Method	Number of Observations	Impacts
1991	Englin and Mendelsohn	TCM	2997	Negative
1994	Mattsson and Li	CV	436	n/a
2002	Kim and Johnson	HPM	2095	Negative

Table 1 Relevant Economic Studies involving Forest Management

The most relevant study, Kim and Johnson (2002), is the bases of this thesis. Their study's results, I believe, foreshadow the expected results more so than Englin or Mattsson's work. I employ the same methodology as Kim and Johnson (2002), but on a far grander scale. The number of home sales used in this thesis research is just under 173,000 and the number of forest cuts is 111,000. Kim and Joshnson (2002) had roughly 2000 observations, four years of home sales, and one forest. The study is able to show a level of variation in forest management styles because the McDonald-Dunn Forest has been divided into seven zones that have different forest management plans. This thesis looks to expand on Kim and Johnson (2002) in a number of ways. Kim and Johnson (2002) were constrained by the number of home sales and age of forest management regimes. They could only look at four years of home sales, restricting their analysis of the impact that the forest management has over time. My dataset has 26 years of home sales, allowing for the estimation of forest activities through time. This study is aided by the WSDNR forest practice data set that has over 40 forest characteristics, including data for total board feet extracted from the site, the size of the site in acres, type of harvest method, and 36 other forest characteristics and management techniques. Aside from the benefit of the WSDNR data set, this thesis shows the impact of variable distance from forest cuts, not just variable time, like Stetler, Venn and Calkin (2010). The one method that this thesis does not apply is the view shed analysis for determination of sight of forest that Kim and Johnson (2002) apply. With more data and greater detail in our data set, this thesis will take a major step forward, being the first true evaluation of the impacts that forest cutting methods have.

III GEOGRAPHIC INFORMATION SYSTEMS, STUDY AREA, AND DATA ANALYSIS

This chapter describes the forest and population of the study area in this thesis as well as describing data sets used and methods employed using GIS analysis. The first section is a discussion of GIS and how it has been used in economic research and how this thesis fits in to that history. The second section is a brief discussion of the population and forest coverage of the study areas and description as to why the specific study areas are used. Section 3 discusses the GIS methods and model used to extract the desired information for this work. Section 4 describes the two data sets being used.

3.1 GIS and Hedonic Research

Natural Resource Economics has evaluated a wide range of resources using GIS. With the aid of GIS, economists have been able to evaluate the economic value of pollutants affecting an area's air, noise and water (Din et al. 2001, Chay and Greenstone 2005, Metz and Clark 1997, Pope 2008, and Leggett and Bockstael 2000), as well as the effect of local crime rates (Linden and Rockoff 2008 and Pope 2008b). GIS provides access to data sets that give hedonic studies a more in-depth and detailed analysis of impacts that happens in the environment. To complete data collection that matches the detail that GIS gives to the already detailed home sales data sets would be expensive, time consuming and not as effective. Parameter and Pope (2012) in their review and recommendations for completing a proper hedonic study cite GIS as a crucial tool.

GIS gives hedonic studies the ability to add spatial characteristics to the analysis. The use of buffering around the geocoded home sales gives a new depth to hedonic studies. Hedonic studies are severely prone to major omitted variable bias (Parameter and Pope 2012). The use of buffering has aided studies like Heintzelman and Tuttle (2012) and Sander, Polasky and Haight (2010). Using buffers ranging from 0.5 miles to 10 miles Heintzelman and Tuttle (2012) produced data for the number of wind turbines in their buffer region and simple yes or no data for the existence of a turbine within a buffer region. Sander, Polasky and Haight (2010) used buffers to measure the amount of urban tree cover inside buffers of 100m to 1000m. Using the buffers to calculate the total the percentage of the buffer regions that were forested, Sander, Polasky and Haight (2010) estimated the forest impacts on the local real estate market. With the help of GIS, they found a non-linear relationship between forest cover percentage and home values (Sander, Polasky and Haight 2010).

GIS can aid hedonic research with more detail then counting and summing specific observations within a buffer distance. In their hedonic study of landscape differences, Geoghegan et al. (1997) used GIS to generate the land characteristics data used in their study. They extracted information described "complexity of landscape types", "human land conversion" amounts and the "degree of parcel land division" (Geoghegan et al. 1997). In their evaluation of urban green space in China, Kong, Yin, and Nakagoshi (2007) added neighborhood characteristics to their hedonic model. Their model included information like ease of access to parks, plazas, and local forests, distance to factories, and number of universities and schools in the surrounding area.

3.2 Study Area

Western Washington has been undergoing major land conversion from forestland to new uses like homes and agriculture (WDNR 2009). A report from the WDNR states that from 1988 to 2004 all the counties in the study have exhibited conversions of their forested land. The amount of land use conversion is projected to increase due to population growth and urbanization (WDNR 2009).

Washington has seven million people living in the state with most of the population living in western Washington (OFM 2015). The population of all the counties in the study area is just over 1 million in 2014 (OFM 2015). The data from the Washington Office of Financial Management shows that the counties in the study area have a dispersion of population totals starting from Wahkiakum with 4,000 to high population areas like Whatcom (200,000) and Thurston (250,000) counties.

The conversion of the forests in western Washington is expected to increase due to the increased demand for non-forested land across the whole western Washington region (WDNR 2009). The counties in the study, except Island and Pacific, have 500,000 or more acres of forested land (WDNR 2009). The majority of the study area are the most forested areas in the state (WDNR 2015). The data regarding the study area from the WDNR (2015) reports that majority of all the state owned and managed forests are located within the study area. This occurrence aids my study, because people are moving and expanding into more forested areas allowing for more homes to potentially be located near timber activities (Radeloff, 2005). The growth of the “wildland-urban interfaces” (WUI) in Washington State is one of the fastest growing expansions in the nation (Radeloff, 2005, Cohen et al., 2015). Increasing pressure on forests and greater homes in major forested areas because of the increase of WUI's create new management problems for state forest manager.

3.3 Data Set Descriptions

There are two data sets that were constructed to complete this research. The first data set is the home sales that have been acquired by the Central Washington Economic department through the Real Market Data Inc., a company that compiles assessor and county courthouse property data for western Washington. The second data set used in this work is the permitted forest cuts GIS on Washington Department of Natural Resources (WDNR) owned lands, titled Washington State Forest Practices Application.

3.3.1 Home Sales

The areas being studied can be seen below in Figure 1. Across 10 counties of western Washington (Clallam, Cowlitz, Grays Harbor, Island, Jefferson, Pacific, Skagit, Thurston, Wahkiakum, Whatcom) there are about 171,000 house sales from 1986 to 2012, all represented by a point feature on the map. The area being studied is dictated by these sales observations, rather than the locations of the Washington DNR forestry data. The counties being studied are among the top producers of timber in the state. The forest cuts span from 1987 to 2015 and there are multiple types of forestry practices that occur across the study areas. DNR has nine different classifications, discussed below.

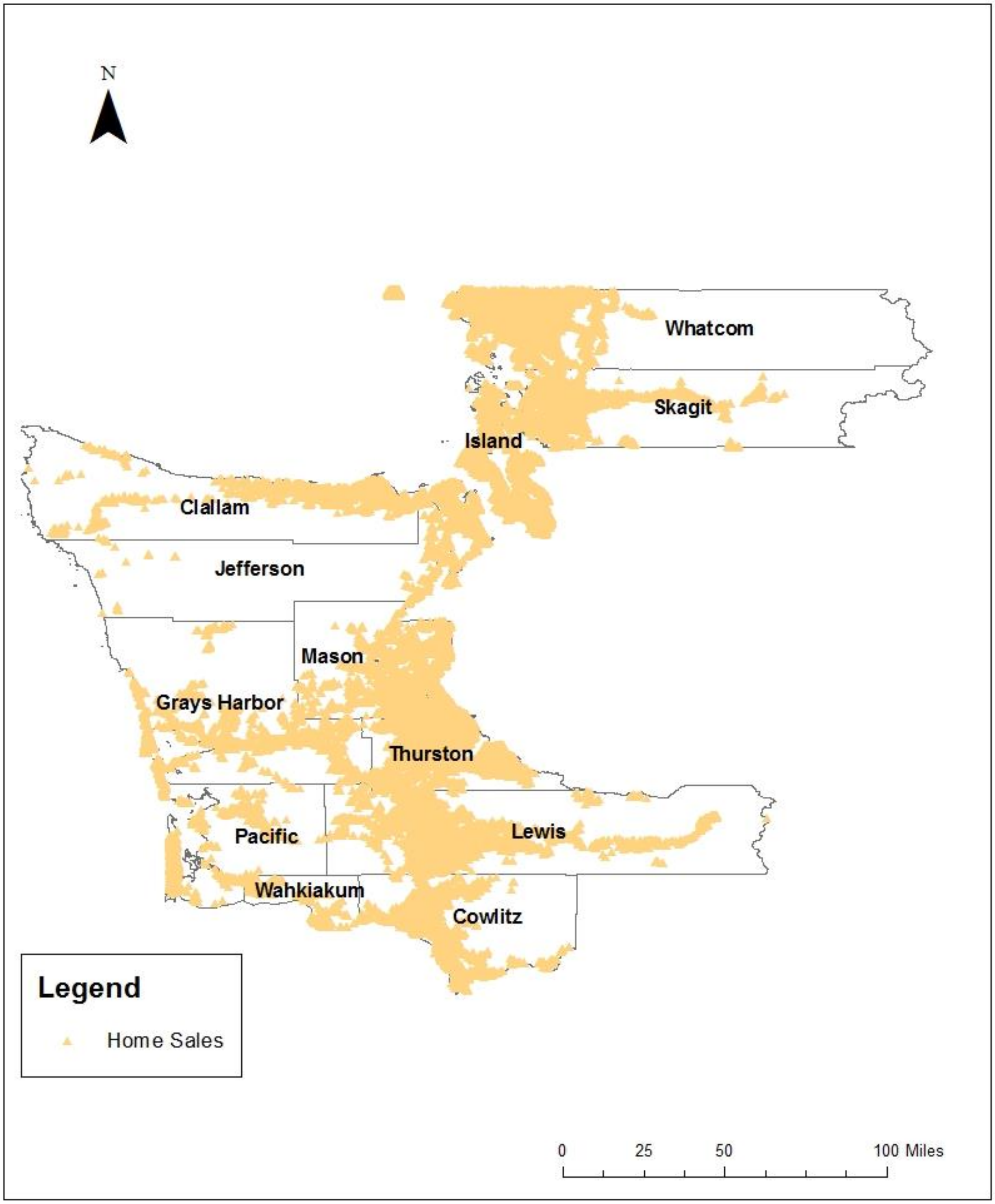

Figure 1 Home Sales Across western Washington

There are 171,141 home sales across Clallam, Cowlitz, Grays Harbor, Island, Jefferson, Lewis, Pacific, Skagit, Thurston, Wahkiakum, and Whatcom County bought from Real Market Data Inc. For this data set to be used in the GIS methods, discussed later in this section, the home sales needed to be Geocoded. The Geocoding process was completed by Logan Blair (2015) in his thesis "The Economic Impacts of Forest Pathogens in Washington State: A Hedonic Approach." Geocoding is the process of plotting a location in a GIS system. This methodology requires a range of address and locations to input into a geocoder created for the area that plots the information in a GIS. The more specific the address information is, the less spatial error there is from the geocoding process. Blair (2015) used the ESRI ArcGIS 10 program's geocoder, the address information given in the home sales data set and the U.S, Census Tiger Lines road files to plot all the home sales in ArcGIS.

There are potential errors from the geocoding process, due to errors in the home sales datasets address information. Through the process of geocoding, ArcGIS produces a score for the goodness of fit of the point plotted. Blair (2015) uses these scores and a random sampling of a range of scores (41-50, 51-60, 61-75, and 76-90). Tables 2 and 3 below are extracted in full from Blair (2015) and describe the score range and errors of the geocoding process found from his random sampling quality checks. The amount of errors decreases as the match score increases, but this also reduces the number of observations. This relationship is accurately shown in Table 3, as score increases the addresses remaining decreases. Blair (2015) concludes since the errors from his tests showed very little errors from scores >60, he subset the home sales based on scores of 61 or greater. This subsequent subset of 61 or greater was further cleaned and edited by Blair (2015). The final cleaned useable single home sales data points used totaled 171,141 and is the home sales data set used in this thesis work.

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

Table 2 : Errors within Score Range (Blair 2015 pg. 29)

Allowed Scores	Percent Matched at given leve(%)l	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

Table 3 Observation per Allowed Score Criteria (Blair 2015 pg. 29)

The WDNR supplies the Washington State Forest Practices Application data set through their public GIS portal (Washington Department of Natural Resources, 2011). This data set is open to the public and it depicts as polygons the forest practices in

Washington State from 1995 to 2011 The forest practice data set can be seen below in Figures 2 and 3..

3.3.2 Washington State Forest Practices Application (All)

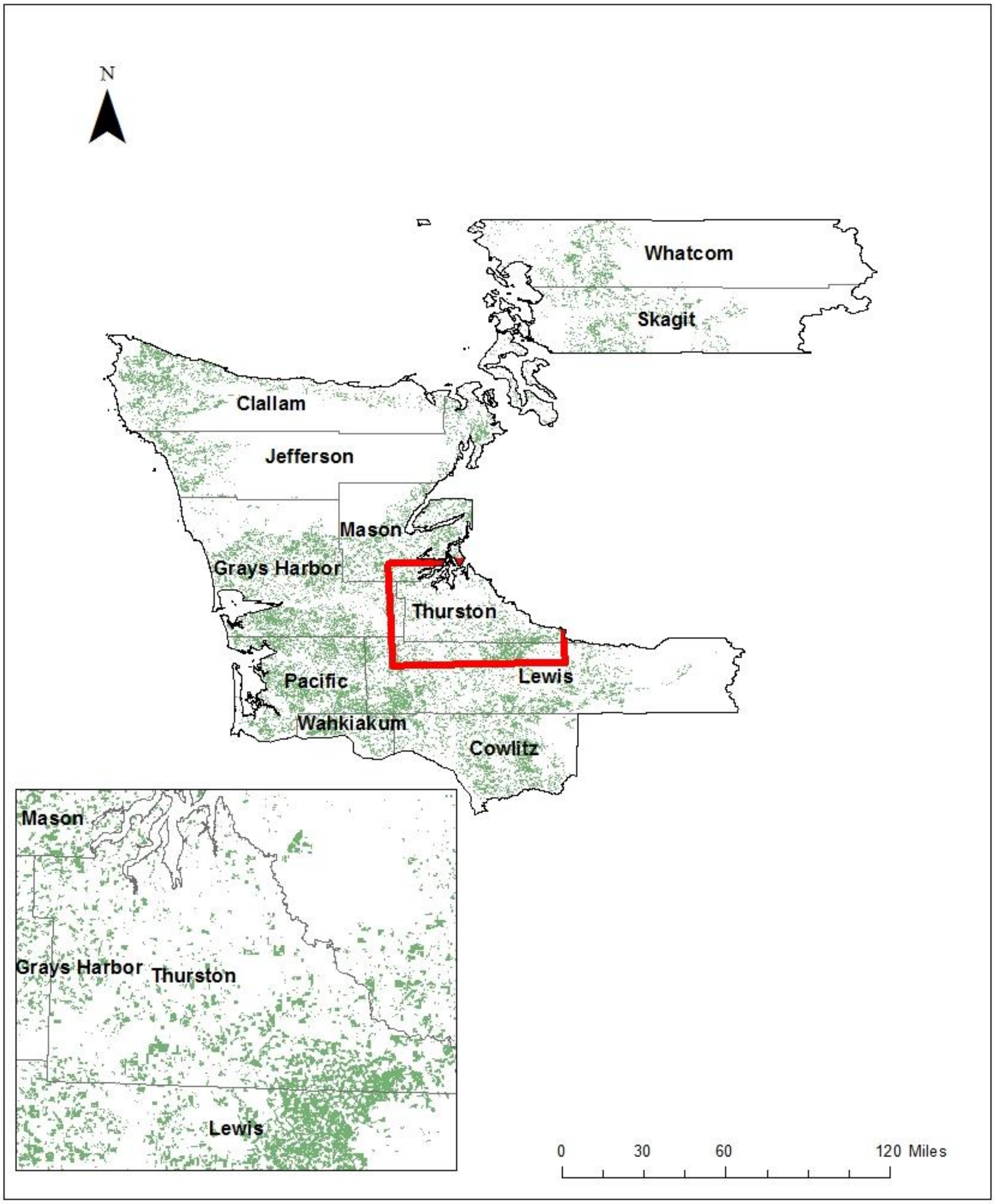

Figure 2 Even-age *Washington State Forest Practices Application*

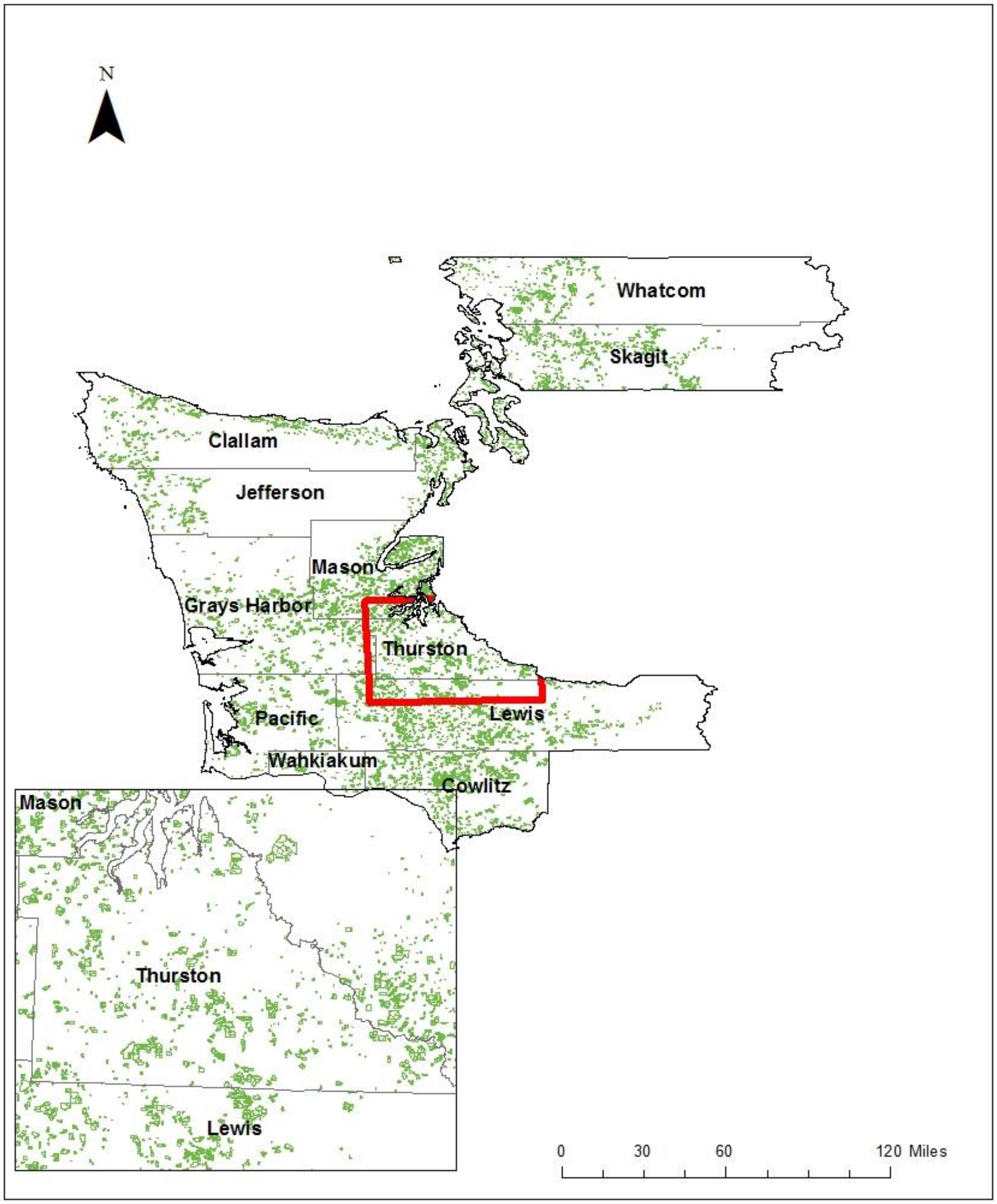

Figure 3 Uneven-age *Washington State Forest Practices Application*

The total dataset has about 165,600 forest practices listed for the entire state. Since the areas that can be analyzed are restricted do to home sales, there are only 111,000 in the study area.

The data set provides information on a wide variety of information regarding what was done on the forest lands. The information provided include data on the creation of forest roads, use of pesticides and air spraying in the forests, and variables regarding proximity to sensitive habitats. Of all these variables, the most crucial are the forest harvest type, forest harvest area, forest harvested estimated volume, application effective date and application decision. These five variables are the most important because they allow for greater data cleaning and classification. This work is only concerned with forest cut applications that occurred, meaning the data that had been listed as disapproved applications were immediately dropped. The last major data cleaning step that was completed was to remove all the forest cut decision dates that occurred after a home's sales date. Forest practices that occurred prior to a home sale would not have any impact in the sale price. In order to measure the treatment effect on the sales price a home, only the forest cuts that occurred prior to a home's sale data within the buffer distance were kept.

The variable for the different forest cutting methods titled forest harvest type has ten potential values. The values include *Even-age*, *Uneven-age*, *Salvage*, *Right of way*, *No Harvest* and then five dual classifications that are combinations of the first four methods. This work's focus is only on the Even and uneven-age practices. I reclassified all the observations into three categories; 1 – all cuts using even-age methods, 2 – all uneven-age methods, 3 – everything else.

3.4 GIS Methods

To measure the economic effect of the forest practices, the data sets must be overlaid in a GIS. In this work ArcGIS was used to find forest cuts that are within the designated buffer zones (0.5km, 1km, and 1.5km) around the home sales. Prior to any buffers being drawn the home sales data set was split apart using the split by attribute (SBA) tool created by USGS (Fox, 2015). This tool is an external tool that takes any vector data and subsets that vector by any field in the attribute table. For this tool the sale county and then the sale month were used. The data set needed to be split into smaller groups for faster processing and the use of county and sales monthly seemed adequate. There were some unforeseen outcomes from this process that did not alter the analysis, but created some data management issues; these will be discussed more in a later section. Each home sale is an observation and a series of buffers were drawn around every home sale. For every home sale, there are three separate buffers that were used. The exact GIS model and tools used to draw the buffers can be seen below in Figure 6. For the buffering model and the intersect model I had to use the iterator function of ArcGIS's Model Builder. This function allowed the model to process through the 333 files that were produced for each county after using the SBA tool.

Figure 4 shows how the buffers and forest cuts are interacted with each other. In the example, below the forest cut polygon is only partially within the 0.5km buffer, but is entirely within the 1km buffer. To extract the entire home sales information and the relevant forest cut information the intersect tool in ArcGIS 10 was used. This tool acts as a spatial one to many join and combines all the attribute of each individual forest cut to the home sale observation and produces the amount of area that the forest cut has within the buffer region. Looking at the example below in Figure 4 the forest cut would report a portion of the acreage for the 0.5km buffer, while the 1km buffer region would report the full acreage.

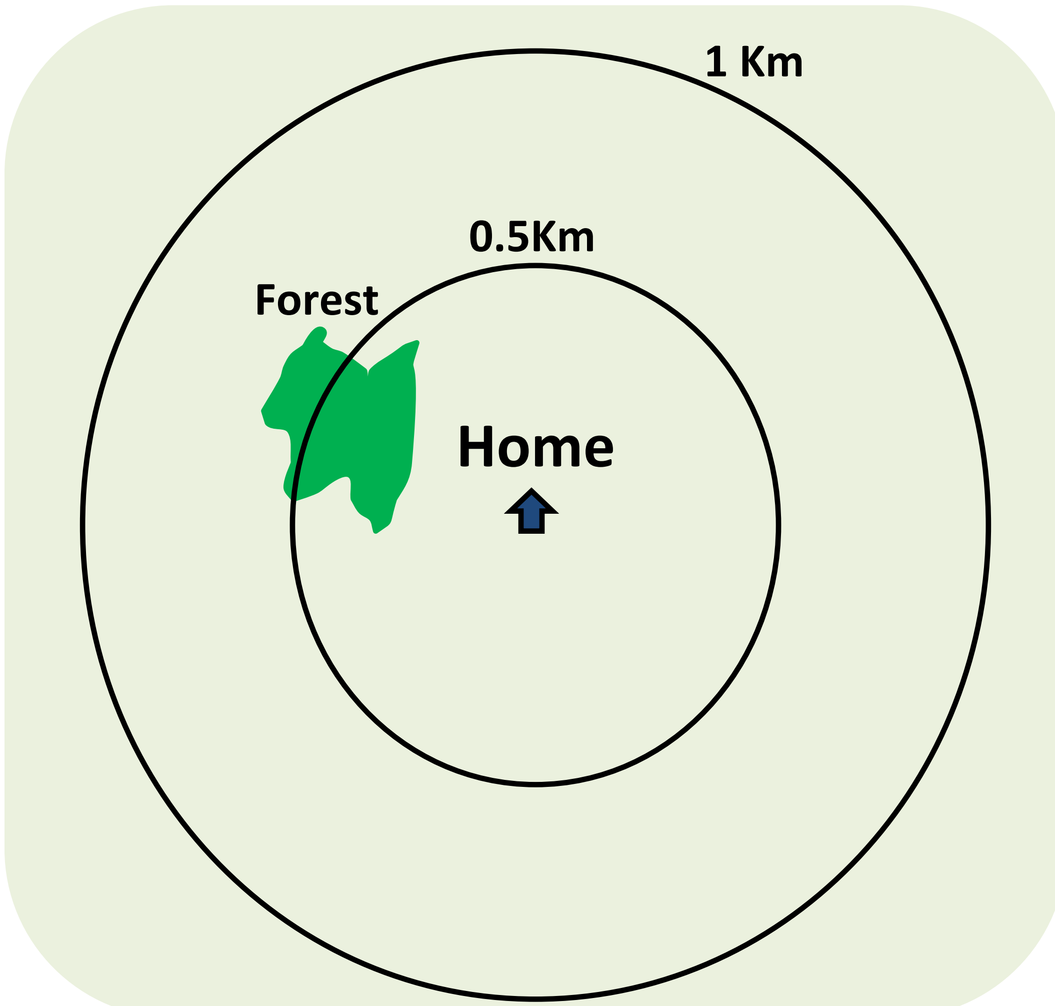

Figure 4 Buffer Tool Example

The final step was to export the intersected data into comma separated files (csv). ArcGIS did not have a tool that would work efficiently with the size and number of files that needed to be exported. After researching alternative methods, the use of

Quantum GIS (QGIS) and an external tool *Batch Save Layers* (Spiers 2016) was used to complete the final task.

For a graphical depiction of the GIS workflow and the exact models used look below in Figure 5, 6, and 7. Figure 5 depicts the workflow beginning with the pre-split data all the way through the intersection and export of the data to csv files.

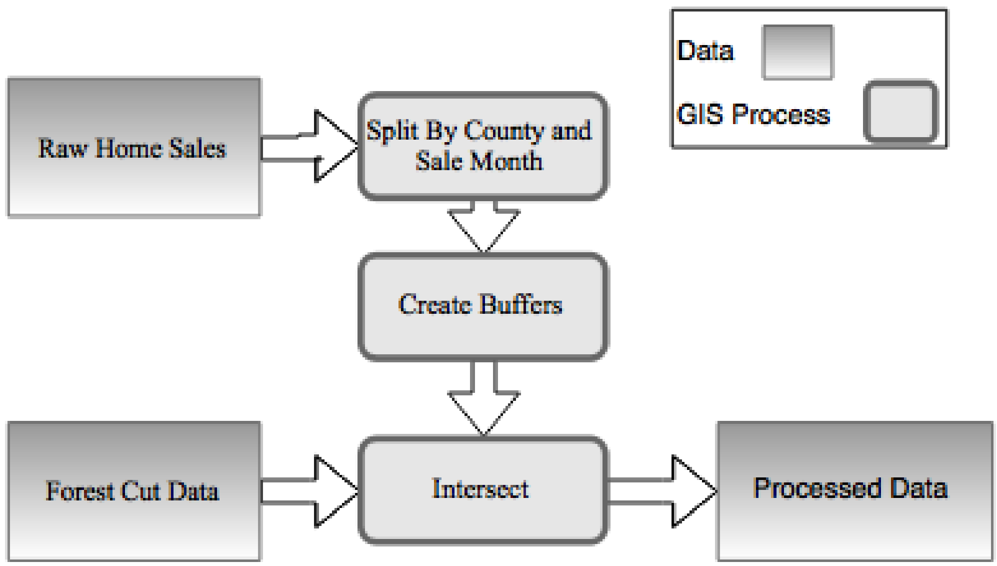

Figure 5 GIS Work Flow

After the GIS data was complete it reduced my sample size down to 141,070 homes. The majority of the lost sales were due to the forest practice data being after a home's sale date and the lack of homes having any forest cuts near them. Table 4,below, shows the summary statistics for the homes in this thesis. The CPI1 variable is the real prices set to 1995 dollars using the West Urban Region Home Sales CPI (Bureau of Labor Statistics, 2017). As seen below the median home Is $169,000, 1508 ft^2, 3 beds, 23 years old and is in a city boundary.

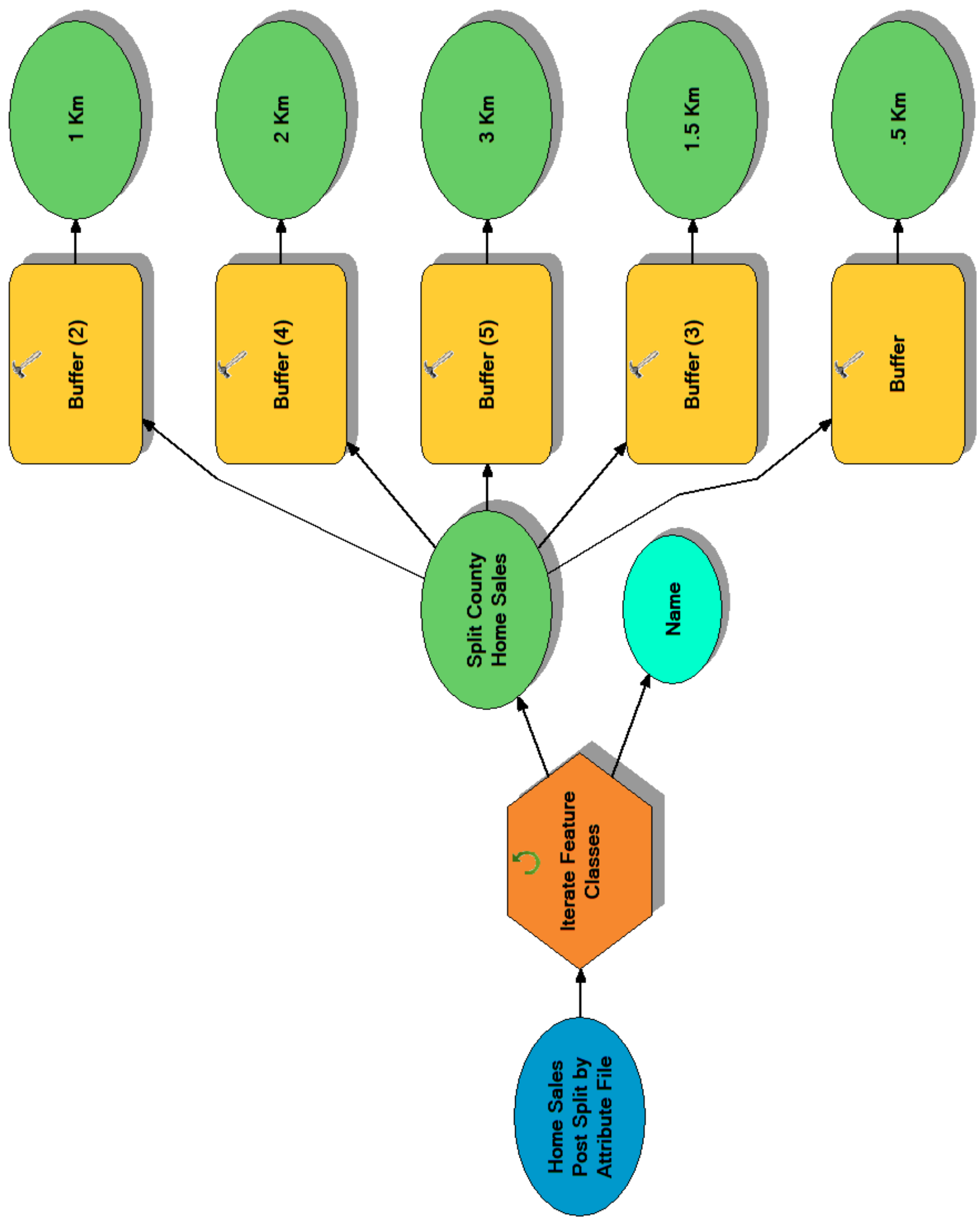

Figure 6 Buffer Model

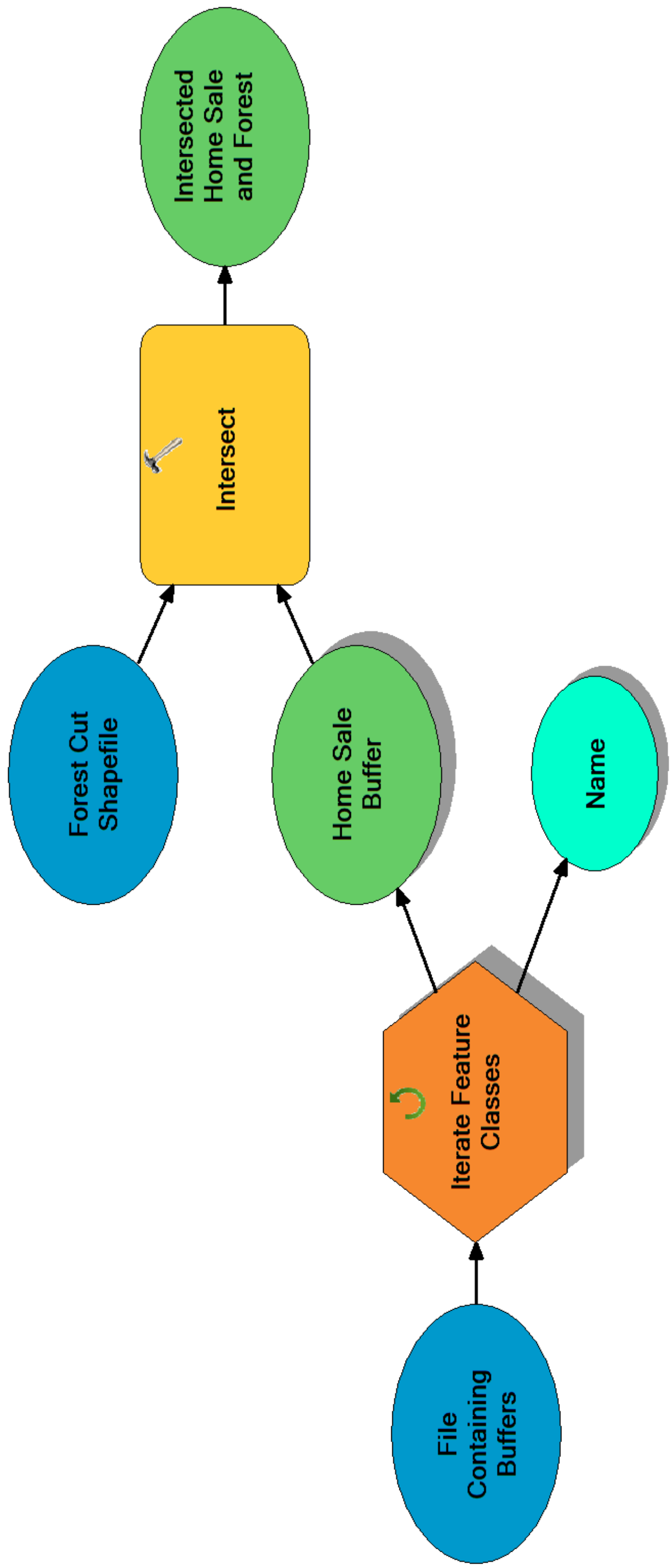

Figure 7 Intersect Model

Table 4 Home Sales Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Median	Max
SALEPRICE	143,070	203,033	139,614	37,500	169,000	3,800,000
ACRES	143,070	1.144	4.597	0.000	0.000	283.800
SqrFeet	143,070	1,615	592.727	205	1,508	31,232
Bedrooms	143,070	2.916	0.738	1	3	9
Age	143,070	29.690	24.801	0	23	265
City	143,070	0.554	0.497	0	1	1
CPI1	143,070	160,972	95,680	46,572	135,990	2,732,004

Tables 5-7 show the summary statistics for the number of acres that is within each buffer region. In all buffer regions, their exists more even-age cuts then uneven-age. While the max cut area in almost all time periods across all the buffers is larger in the uneven-age methods, the average cut area is larger for even-age methods. This hints at a potentially large variation in the total cut area for uneven-age methods.

Table 5 0.5 km Buffer Summary Statistics (Acres)

Time Sold After Timber Activity	Even							Uneven						
	N	Average	Median	Q1	Q3	Min	Max	N	Average	Median	Q1	Q3	Min	Max
30 Days	641	0.027	0	0	0	0	8.578	211	0.009	0	0	0	0	10.631
6 mos.	2983	0.129	0	0	0	0	12.360	892	0.040	0	0	0	0	19.063
1 Year	3470	0.150	0	0	0	0	12.560	1028	0.043	0	0	0	0	15.163
2 Year	6775	0.362	0	0	0	0	12.169	2033	0.102	0	0	0	0	15.291
3 Year	6484	0.386	0	0	0	0	19.613	2073	0.107	0	0	0	0	14.854
4 Year	5985	0.330	0	0	0	0	12.237	1999	0.106	0	0	0	0	15.161
5 Year	5487	0.282	0	0	0	0	11.719	1994	0.102	0	0	0	0	15.163
6 Year	4982	0.261	0	0	0	0	11.660	1896	0.099	0	0	0	0	19.173
7 Year	4493	0.233	0	0	0	0	18.484	1914	0.095	0	0	0	0	19.173
8 Year	3941	0.179	0	0	0	0	12.571	1765	0.163	0	0	0	0	14.854
9 Year	3284	0.152	0	0	0	0	9.850	1465	0.120	0	0	0	0	15.805
10 Year	2732	0.134	0	0	0	0	17.581	1219	0.118	0	0	0	0	15.862
15 Year	4781	0.329	0	0	0	0	26.264	2616	0.262	0	0	0	0	23.148
20 Year	130	0.008	0	0	0	0	6.983	41	0.002	0	0	0	0	10.655

Table 6 1 km Buffer Summary Statistics (Acres)

Time Sold After Timber Activity	Even							Uneven						
	N	Average	Median	Q1	Q3	Min	Max	N	Average	Median	Q1	Q3	Min	Max
30 Days	2216	0.140	0	0	0	0	19.002	693	0.055	0	0	0	0	40.606
6 mos.	9422	0.656	0	0	0	0	20.589	3300	0.274	0	0	0	0	42.686
1 Year	10827	0.773	0	0	0	0	29.612	3812	0.283	0	0	0	0	42.746
2 Year	19091	1.592	0	0	0	0	27.903	7287	0.608	0	0	0	0	42.815
3 Year	18249	1.545	0	0	0	0	32.697	7191	0.627	0	0	0	0	43.117
4 Year	17202	1.410	0	0	0	0	26.659	6994	0.610	0	0	0	0	42.827
5 Year	16208	1.298	0	0	0	0	30.320	6899	0.594	0	0	0	0	42.746
6 Year	15039	1.212	0	0	0	0	27.028	6577	0.609	0	0	0	0	42.149
7 Year	13597	1.077	0	0	0	0	35.452	6569	0.590	0	0	0	0	43.086
8 Year	12204	0.930	0	0	0	0	24.465	5903	0.713	0	0	0	0	43.083
9 Year	10447	0.789	0	0	0	0	33.036	4993	0.588	0	0	0	0	48.269
10 Year	8198	0.622	0	0	0	0	24.465	4038	0.532	0	0	0	0	48.251
15 Year	12562	1.462	0	0	0	0	43.725	7370	1.298	0	0	0	0	55.130
20 Year	512	0.057	0	0	0	0	18.060	227	0.014	0	0	0	0	12.453

Table 7 1.5 km Buffer Summary Statistics (Acres)

Time Sold After Timber Activity	Even							Uneven						
	N	Average	Median	Q1	Q3	Min	Max	N	Average	Median	Q1	Q3	Min	Max
30 Days	4304	0.315	0	0	0	0	21.754	1408	0.137	0	0	0	0	77.403
6 mos.	17809	1.577	0	0	0	0	28.250	6424	0.659	0	0	0	0	80.206
1 Year	20125	1.855	0	0	0	0	52.908	7517	0.711	0	0	0	0	81.355
2 Year	33765	3.649	0	0	0	0	50.196	14054	1.496	0	0	0	0	79.170
3 Year	32262	3.489	0	0	0	0	48.914	13693	1.528	0	0	0	0	79.302
4 Year	30147	3.217	0	0	0	0	38.559	13365	1.466	0	0	0	0	79.471
5 Year	28533	3.033	0	0	0	0	47.508	13135	1.430	0	0	0	0	79.511
6 Year	26593	2.868	0	0	0	0	37.004	12443	1.460	0	0	0	0	79.896
7 Year	24133	2.612	0	0	0	0	51.263	12121	1.397	0	0	0	0	79.471
8 Year	21752	2.327	0	0	0	0	38.260	10887	1.594	0	0	0	0	79.385
9 Year	18499	1.932	0	0	0	0	33.572	9211	1.294	0	0	0	0	95.271
10 Year	14518	1.475	0	0	0	0	33.630	7233	1.069	0	0	0	0	78.786
15 Year	18839	3.534	0	0	0	0	58.667	11835	2.691	0	0	0	0	79.406
20 Year	958	0.151	0	0	0	0	18.764	388	0.029	0	0	0	0	21.764

IV JOURNAL ARTICLE

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

Kaleb Javier *

Abstract

Washington State is one of the nation's leaders in timber production. This paper establishes literature gap regarding the economic impacts of forest timber management methods. In this research, I employ a data set of 170,141 home sales across eleven counties of western Washington to estimate the impact that even-age and uneven-age forest cutting methods have on the local real-estate market. I estimate two sets of hedonic fixed effect regression models to control for omitted variable bias and spatial autocorrelation. The results show statistically significant impacts on property values for both cutting methods, adding important information for forest managers.

Keywords: Even-age, Uneven-age, Clear-cut, Hedonic, Environmental Economics, Revealed Preference, Environmental Impact, Forest

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4.1 Introduction

Starting a harvesting operation begins with many decisions prior to any tree falling (Florence 1977). Even-age cuts and uneven-age cuts are the two most common methodologies to harvest timber. The differences between these two operations differ in all manners, but the most observable difference is the post-harvest effect (Bliss 2000). Even-age methods cut the tree stands and only leave bare land which is predominately perceived as deforestation (Bliss 2000). The most controversial method of even-age cuts is clear-cutting (Boughton 1990).

Clear-cutting for timber is an assortment of personal benefits and social challenges to forest industry. Although not the focus of this paper it is important to note that the practice of clear-cutting has a long history worldwide. The use of clear-cutting in Europe alone is centuries old (Keenan and Kimmins 1993). Clear-cutting is the most economically cost-effective method of forest harvesting that can be done (Smith 1972). Clear-cutting allows for more profits to be extracted, but it is followed with much more scrutiny and public animosity then the other uneven-age methods. People see these operations as leaving scars on the landscape and causing major environmental harms (Keenan and Kimmins 1993; Ribe and Matterson 2002). Across the United States, there is a largely negative view of clear-cuts (Bliss 2000). Multiple surveys and ethnographic studies have shown that people from the Pacific Northwest to the Southern United States have a negative perception of the practice (Bliss 2000).

There are traditionally two classifications for cutting forests. Foresters and silviculturists call these different types of cutting, “regeneration methods” and the two groups are even-aged and uneven-aged (Boughton 1990). These two groups are further divided into five different types: clear-cut, seed tree, shelter wood, single tree selection, and group selection (Boughton 1990).

These methods are used to create tree stands that consist of same species of trees with all similar age (Nyland 2016). Clear-cutting involves harvesting all the standing trees in the designated area in one full operation (Boughton 1990). The last two even-aged methods are seed tree and shelter wood. These approach involves cutting away all the trees, except for the desired mature trees so they can leave seeds to produce a new stand (Nyland 2016).These practices involves more site preparation and management to ensure that competing shrubs and trees do not inhibit or harm the growth of the desired seedlings (Nyland 2016).

The two methods for uneven-aged cutting methods are single tree selection and group selection. Single tree involves cutting trees that are close to the end of life and are the healthiest and highest quality the particular tree can be and harvesting them (Nyland 2016). The second method, group selection, involves cutting small groups of trees from a stand to stimulate the surrounding forest to start regenerating (Lamson and Leak 2000). This method mimics the same effect small scale disturbances have on a forest (Lamson and Leak 2000). This approach requires a large amount of management and monitoring before harvest, and levels of harvest can be controlled to create sustainable yields (Nyland 2016).

Washington State being a major timber producer in the country, applies both methods of cutting. Washington State is among the top producers in the nation for timber and is ranked fifth for timber employment and wages. (Bureau of Labor Statistics 2014). Washington State produced just over 3.2 million board feet of timber in 2014 and of the 39 counties in the state, 32 of them is involved in the timber industry (WSDNR 2015). Lewis, Pacific, and Greys Harbor are the top three timber producing counties in Washington and are among the majority of timber producing counties located in western Washington (WSDNR 2015). The data regarding forest practices in Washington shows roughly 106,000 permitted even-age cuts and almost 32,000 uneven-age permitted cuts since the late 1980s. Washington State is an ideal study area to estimate the impacts of the different forest timber methods used by foresters and forest managers.

Prior research regarding the impacts of even-age and uneven-age methods is scarce. The earliest research evaluates people's perceptions of forests rather than the cutting methods practiced. Ribe and Matteson (2002) in their perception research surveyed people in different ideological groups in western Washington and Oregon about their views of different forestry methods and the spotted owl. Their research highlighted a trend of strong public opposition to clear cuts in the United States. They concluded that new forest practices in the United States could make clear-cutting and other old forestry practice outdated or even outlawed (Ribe and Matterson 2002).

The past literature describes negative perceptions for even-age cutting methods. The most common reported reason was the impact to the aesthetics of the forest scenery (Palmer et al. 2005, Ribe and Matteson 2002; Bliss 2000). Palmer et al. (2005) specifically found that people disprove of the sight of clear-cuts at any given intensity in a forest scene. The next most common reason in the literature was environmental and ecological concerns (Ribe and Matterson 2002; Bourke and Luloff 1994).

In economics, the research evaluating forests and forest timber practices are limited. The earliest of works use the Travel Cost Method (TCM) and Contingent Valuation Method (CV). TCM is a revealed preference method that uses surveys and asks the visitors of forests or other public access goods questions about distance traveled, cost of travel, income and many other socio-economic questions (Loomis and Eichhorn 2000). Using the responses from their survey researchers can estimate a cost to traveling to the location, in turn producing a Willingness-to-Pay (WTP) estimate for the location. Contingent Valuation method is a stated preference method of measuring the WTP of forest users, like hikers (Hanemann 2017). This method's uses surveys like TCM, but instead of estimating the cost of travel, the surveyors ask explicitly how much visitors or users of a public good their WTP is. CV and TCM studies have estimated the WTP for the recreational, existence and ecotourism benefits of forests and other natural areas (Dwyer et.al. 1983, Englin and Mendelsohn 1991, Menkhaus and Lober 1996 Scarpa et al. 2000).

The earlier literature shows a positive value of the WTP for forests. Dwyer et.al. (1983), used TCM to evaluate the WTP of visitors to three different forests in their study was close to $10 dollars on average per visitor. Forests with higher WTP had more attractions for visitors, were closer to user's home and had less deterioration of forest

(Dwyer et.al. 1983). Englin and Mendelsohn (1991) evaluated people's preferences for different forest practices and amenities of the forested area. They found the willingness to travel for forests that had diverse forest characteristics and amenities. Englin and Mendelsohn (1991) found that the average person in their study was willing to spend $2.61 for every extra mile of old-growth forest in the area they were traveling to. In a TCM study that evaluated the WTP for Costa Rica's tropical forests Menkhaus and Lober (1996), found an average visitors WTP of about USD $1150. Scarpa et al. (2000), used the CV method to evaluate the recreationalists WTP fort the creation of new Nature Reserves in Ireland. They estimated that the induction of more forests into the Irish nature reserves system has led to an increase of about 7.5 million pounds to the social benefit of Ireland (Scarpa et al. 2000).

Lindhjem and Mitani (2012) used the CV method to evaluate forest owners' willingness to accept payment to conserve their forests rather then cut them in Norway. They found an average willingness to accept payments of NOK 1800 per hectare of forest and argue that large costs can be avoided through selective targeting of forest owners. Haghjou et al. (2016) used the CV method to evaluate the economic value of the Arasbaran Forests in Iran. The respondents' education attainment, income levels, number of visits to the forests, and their friendly attitudes the forests had positive impacts on WTP for conservation of the forest (Haghjou et al. 2016).

Robinson, Hite and Hanson (2016) used the TCM to evaluate the responses of 563 of visitors the Gulf Coast Region of the US. They estimated the mean WTP for the existence of pre-Deepwater Horizon Spill beach quality was $29.18 per person. Their findings reported that “visitors receive eight times more benefit” from having long term continual access to quality beaches in Gulf Coast. Bertram and Larondelle used the TCM to evaluate an urban forest in Berlin, Germany. Their results found a “consumer surplus of 14.95 € per visit” and that there are significant differences in demand elasticities when origin of visitor is considered.

This paper uses the Hedonic Property Model (HPM) to measure the exogenous effect that forest timber activities have on the local real estate market. In a similar fashion to this papers methods Tyrväinen, and Miettinen (2000) estimate the WTP for an urban forest and its services provide to the people in Salo, Finland. They found the closer people lived to the urban forest, the greater the WTP (Tyrväinen, and Miettinen 2000).

In the economic literature, there are only three studies that evaluate forest timber method impacts and peoples WTP. The earliest research that applies to this thesis is survey methods like TCM and CV. Englin and Mendelsohn (1991) completed a TCM study where they collected overnight camping permits for four United State Forest Service (USFS) wilderness areas in Washington State. Using these permits, they could estimate the WTP of the users of the camp sites in the four USFS wilderness areas. Englin and Mendelson (1991) then combined the permit data with census data and the USFS trail characteristic data for each wilderness area. The study’s focus was not specifically on the impacts of forest practices, but they could derive WTP for the impacts of clear-cutting. In similar fashion to the perception studies discussed earlier, they found negative impacts on the WTP for visitors to wilderness areas that contained trails that had clear-cut activity. They estimated the campers had a WTP of $0.58 per mile of trail that was free of clear-cut activity on the trail (Englin and Mendelsohn 1991). Their results show a clear aversion to clear-cutting.

In a CV study, Mattsson and Li (1994) evaluated the WTP of Swiss forest management techniques. They used the CV method and were able to get 436 respondents from their surveys. The study evaluated the WTP of the sylvicultural practice of replanting post clear-cut and the WTP for tree compositions in the forests. Mattsson and Li (1994) found that people prefer tree stands that seem more "mature" and have a variety of tree species. A major takeaway is that the Swiss people preferred in all cases timber activity management that left a forest with trees meeting the perceptions of a mature and diverse forest (Mattsson and Li 1994). While the study pertains to Swiss forest preferences, the prior socioeconomic literature highlights similar responses by people in the US.

The most similar work to this research has been done over a small area in Corvallis, Oregon. Kim and Johnson (2002) studied the McDonald-Dunn Forest in Corvallis, Oregon and estimated the effects that the local forest had on housing prices in the area. Kim and Johnson (2002) found that a house with a view of a clear-cut had a substantial price decrease, just over $16,000 (1995 dollars), per house on average (Kim and Johnson 2002). This is a substantial decrease in home prices and demonstrates the consumer preference that people do not support clear-cutting activity. It is a powerful empirical result that supports all the perception studies conducted by the likes of Palmer et al. (2005), Ribe and Matteson (2002) and Bliss (2000). Kim and Johnson's monetary impacts are not necessarily transferrable to western Washington, but the direction of the impact should be equivalent.

This work is an extension of the work by Kim and Johnson (2002). From my research, I use the largest data set of home sales and forest practices to estimate the impacts of even-age and uneven-age forest practices in western Washington. This paper uses what I believe is the largest data sets in the forest hedonic research, 172,119 western Washington home sales and 426,000 forest practices in western Washington across 26 years. I also further the analysis by looking at the impact of forests surrounding each home sale out to 1.5 km radius around each home. I estimate multiple models to evaluate the impact the two types of forest cutting methods have over time. The estimated models use census block groups and quarterly year fixed effects to control for regional and time bias in the estimates.

I estimate two models; the first model is similar to that in Kim and Johnson (2002). The simplest of the two model, it measures the impact of a having a cutting method occur within a buffer on real estate values. I expand on Kim and Johnson's (2002) mode0l to show the impact over a 20-year period. The second model is an expansion to the literature and measures the total amount of acreage cut within the specific buffer distances across time. My unique forest data provides the total amount of acreage cut, providing this paper with a level of specificity that has yet to be seen in the economic forestry to date. I find that both methods of cutting, even and uneven, impose moderate to large negative impacts when the cuts were recent in time and show a diminishing impact over a 20-year period.

The next section of this paper discusses the study area and the data used. Section three reviews the methods, specific models used and the empirical issues of my research. Section four presents the results of the research and section five follows with a discussion of the results. The sixth and final section suggests further work and conclusions of the study.

4.2 Study Area and Data

My study area is made up of Clallam, Cowlitz, Grays Harbor, Island, Jefferson, Lewis, Mason, Pacific, Skagit, Thurston, Wahkiakum and Whatcom counties. These twelve counties have a total of 19,097 square miles (Blair, 2015) and a total population just over 1 million in 2014 (OFM 2015). The data from the Washington Office of Financial Management shows that the counties' population totals range from Wahkiakum with 4,000 to high population areas like Thurston (250,000) and Whatcom (200,000) counties. Except for Island and Pacific counties, the rest of the study area has 500,000 or more acres of forested land (WDNR 2009). The study area has the most forested counties in the state (WDNR 2015). The data regarding the study area from the WDNR (2015) reports that majority of all the state owned and managed forests are located within the study area. This occurrence aids my study, because people are moving and expanding into more forested areas allowing for more homes to potentially be located near timber activities (Radeloff, 2005). The growth of the "wildland-urban interfaces" (WUI) in Washington State is one of the fastest growing examples in the nation (Radeloff, 2005, Cohen et al., 2015). Increased presure on forests and greater numbers of homes in major forested areas due to the increase of WUI's create new management problems for state forest managers.

This study uses are two data sets forest practice applications and housing sales data. The Washington State forest practice applications data set is provided by the Washington Department of Natural Resources (WDNR). This data set is an aggregation of all the documented forest permits submitted to WDNR. This data set has been mapped and displays every submitted forest practice permit as polygons. Each polygon represents the actual area cut and the data contains information on all the activity that occurred on that forest. This information includes expected total board feet extracted, total area cut type of cutting methods used and date of cut.

The real estate data used was bought from Real Market Data, a company that specializes in aggregating and selling county assessor and courthouse property data. This data set includes many home characteristic variables other than sale price, such as total home floor area, bedrooms, bathrooms, acreage, home state of buyer and address from 1982 to 2012. The median home is $169,000, 1,508 ft^2, 3 bedrooms, 23 years old and is in a city boundary.

The pivotal spatial representation of the home sales data set was completed in prior research by Logan Blair (2015). Without the geocoding of the home sales, the analysis of this paper would not have been possible. Blair (2015) accepted a geocode match errors of 61% or greater as the final home sale data set. The outcome of Blair (2015) geocoding efforts produced a data set of 170,141 home sales across 26 years for all 12 counties. The geocoded data set produced by Blair (2015) is the home sales used in this study.

A home sales data set that ranges 26 years is heavily impacted by inflation and makes it necessary to standardize the sale prices of all the homes. Using the Consumer Price Index for All Urban Consumers: Housing in West urban provided by the U.S Bureau of Labor Statistics (2017), I adjusted all the home sales to 1995 prices.

The use of buffers ranging from 0.5km, 1km, 1.5km was used on all the home sales and then those buffers were intersected with the forest practice polygons in ArcGIS to add forest characteristics to each home sale.

4.3 Method and Empirical Issues

The goal of this research is to empirically evaluate the impacts that even-age and uneven-age forest cutting practices have on the sale price of a home, while controlling for other determinates of a home's sales price. The theory behind hedonic methodology is a home or any other good's price is a function of its many characteristics. In the case of a home, the sale price is representative of the homes structural make up, neighborhood, and the varying environmental amenities and disamenities surrounding the home. Rosen (1974) in his seminal paper of hedonic research describes products consumers buy as a "bundle" of goods rather than one single good. While every person values homes differently, when considering the real estate market each characteristic of a home that makes up the "bundle" that is a home becomes explicitly defined (Rosen, 1974). The outcome of Rosen's (1974) paper is what is now known as the hedonic price model, for this research the hedonic real estate price model:

$$P(x) = P\ (x_1, \dots, x_n) \tag{1}$$

Where P is the price of a home given, the differentiated products of an estimated fixed value i.e. number of bedroom and total square feet. It is well documented and known that characteristics of a home like size and bathrooms impact the price of the home, there is evidence in past research that suggest that forest practices near homes would be included into a home's sales price. I make two hypotheses in this paper. The first is having a forest activity near homes, particularly even-age, will have an impact on home prices significantly different from zero, and my second hypothesis is as the total area of forest cut increase its effect on a home sales price will be different from zero.

Explicitly the claims are as follows:

Null

$$\mathrm{H}_{\text{Cut Occuring }0}\text{: } \beta_1 \text{ Local Forest Cutting Activity} = 0$$

$$\mathrm{H}_{\text{Cut Area }0}\text{: } \beta_1 \text{ Total Area Cut} = 0$$

And the alternatives

$$\mathrm{H}_{\text{Cut Occuring1}}: \beta_1 \text{ Local Forest Cutting Activity} \neq 0$$

$$\mathrm{H}_{\text{Cut Area1}}: \beta_1 \text{ Total Area Cut} \neq 0$$

To test these relationships takes special care and thought as to how forest cutting practices effects the sales price of a local home. Unlike tree blight and pest's hedonic studies by Blair (2015) and Price et al. (2008) the impact on the surrounding landscape is essentially permanent. Forest cutting, especially even-age methods, leaves drastic lasting impacts on the surrounding land scape. Clear-cutting practices will remove a whole tree stand and only leave stumps creating a large open area. Along with the drastic post-cut impacts, the process of cutting a forest is labor and time intensive. It would not be practical to expect that having these operations close to a home will not have an impact. The aftermath of cutting activities leave the landscape changed for many years, but the size of the local operations must also be taken into account. Having an operation occur within a simple distance measure is a simplistic measure of the impacts of cutting practices. The optimal study is to estimate total cut area near home sales across time and distance. Accordingly, I estimate two separate models of the impact of forest practices. The first model can be seen in formulae (2) and (3). These quantify the impact of the occurrence of any timber activity across time and buffer distance. The difference between (2) and (3) is the level of fixed effect control, explained further below. The second set of regressions can be seen below in formulae (4) and (5). These evaluate the impact that an extra 10 acre cut of either even-age or uneven-age methods has on a home's sale price across the three buffer distance and time. I used the same fixed effect controls in models (2) and (3) to estimate models (4) and (5).

A dataset that is as large and wide-spread as this paper's requires specific control for spatially correlated errors and variation in the home sale prices. For example, a home's price in Thurston county vary for different reasons then the prices in Whatcom county, and these unobservable reasons inject bias into the estimates. The best practices in fixed-effect OLS regressions to control for the regional price variation are to use geographic indices variables. Using GIS and the tiger block groups data set, every home sale was assigned their corresponding census block group. On top of this regional control I interact the census block groups with year quarterly date variables to control for time variation in each respective block group (Zabel and Guignet 2012). Using these fixed effect controls will also reduce the amount of spatial auto correlation. Assigning each home, sales a specific geographic class (census block), the autocorrelation will be controlled, allowing only error correlations within the specific groupings (Dormann et al. 2007). Along with the fixed effect controls of block group by year I produce robust clustered standard errors by clustering on the county that each home sales resides in.

The two models estimated in this paper are functionally the same: pooled regression models that use census block groups and quarterly year groups as fixed effects. The first model measures the percent change of a home's sale price Y, given the occurrence of a forest cut near the home sale X, by the estimated coefficient β_1. The first fixed effect timber cut occurrence model for a home sale i in block p, at time period t:

$$lnY_{ipt} = \beta_1 X_{ipt} + \beta_2 W_{ipt} + \alpha_p + \lambda_t + u_{ipt} \qquad (2)$$

$$lnY_{ipt} = \beta_1 X_{ipt} + \beta_2 W_{ipt} + \alpha_p \times \lambda_t + u_{ipt} \qquad (3)$$

In equations (2) and (3), lnY_{ipt} is the log price of home i in census block p at time period$t$. W_{ipt} is the representation of a long list of the structure variable of a home, like total square feet and number of bedrooms. α_p Is the census block fixed effect and λ_t is the variable for the quarter of the year and the individual error term of u_{ipt}. The functional difference the two regression formulas is the first formula employs a less-restrictive fixed-effect than the second, which adds the product of quarters and block groups to the fixed-effect controls.

The aggregate cut area regression equation for home i in census block p at time period$t$:

$$lnY_{ipt} = \beta_1 A_{ipt} + \beta_2 W_{ipt} + \alpha_p + \lambda_t + u_{ipt} \qquad (4)$$

$$lnY_{ipt} = \beta_1 A_{ipt} + \beta_2 W_{ipt} + \alpha_p \times \lambda_t + u_{ipt} \qquad (5)$$

In equations (4) and (5), all of the variables are the same as in equations (2) and (3), except forA_{ipt}. The variable A_{ipt} is the aggregated area cut in acres. The aggregated cut model also use the sum and product fixed-effect of block groups and quarter. I report both models in the following section across all buffer areas and cut types for 14 time periods. In the rural subset regressions, I only employ the separate time and block group fixed effects because of a lack of observations in some of the block group and time fixed effects.

4.4 Results

Tables 8 through 10 show the results for equations 2 and 3 across the 20-year time-period and different buffer lengths, and tables 11 through 13 present the results for model 4 and 5 discussed earlier. All six tables present the results for even-age and uneven-age cutting methods.

The impact of a forest cutting operation occurring within either distance of 0.5km, 1km and 1.5km of a home sale is negative for both fixed effects models with varying degrees of significance. In Tables 8 and 10, there exists strong statistical significance and moderate to large impacts on a home's sale price for the oldest occurring even-age cuts in the much stricter fixed effect of time by block group. The less stringent fixed effect shows majority of all the even-age results as significant and impacts that range from approximately -4% to approximately -8%. In terms of the median house price it equals a loss of between $6,627 to $12,993 for simply having an even-age forest method within any of the buffer ranges. The more restrictive fixed effect even-age results report similar magnitudes on the few statistically significant results, but as the buffer distance increase the magnitudes of the negative impacts begin to lessen. The less restrictive model has lasting negative impacts that persist through time and distance.

Table 8 Impact of Timber Activity within Buffer 0.5 km

Dependent Variable = Log(Sale Price)	Impact of Timber Activity Within Buffer 0.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)
30 Days	-0.075	-0.286	-0.058	-0.094
	0.088	*0.380*	*0.046*	*0.092*
6 Months	-0.033**	-0.118	0.005	0.213
	0.015	*0.130*	*0.019*	*0.179*
1 Year	-0.052**	-0.053	0.009	0.141
	0.023	*0.072*	*0.049*	*0.150*
2 Year	-0.049***	-0.083	-0.003	0.055
	0.014	*0.078*	*0.036*	*0.151*
3 Year	-0.048***	-0.025	-0.015	0.005
	0.011	*0.059*	*0.035*	*0.145*
4 Year	-0.047**	-0.054	0.002	-0.034
	0.019	*0.070*	*0.031*	*0.118*
5 Year	-0.050***	-0.038	-0.022	-0.103
	0.019	*0.073*	*0.019*	*0.106*
6 Year	-0.058**	-0.075	-0.029*	-0.140
	0.023	*0.072*	*0.015*	*0.088*
7 Year	-0.025	-0.096*	-0.019	-0.065
	0.025	*0.058*	*0.019*	*0.065*
8 Year	-0.067**	-0.084*	-0.041**	-0.160***
	0.026	*0.043*	*0.018*	*0.051*
9 Year	-0.064**	-0.078***	-0.037**	-0.159***
	0.025	*0.029*	*0.018*	*0.049*
10 Year	-0.064**	-0.069***	-0.049***	-0.156***
	0.029	*0.025*	*0.018*	*0.046*
15 year	-0.067**	-0.063**	-0.056**	-0.153***
	0.030	*0.026*	*0.022*	*0.058*
20 Year	-0.068**	-0.063**	-0.059***	-0.152**
	0.030	*0.026*	*0.022*	*0.059*

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

Table 9 Impact of Timber Activity within Buffer 1 km

Dependent Variable = Log(Sale Price)	**Impact of Timber Activity Within Buffer** 1 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(5)	(6)	(7)	(8)
30 Days	-0.073**	-0.158	-0.048	-0.074
	0.034	*0.282*	*0.072*	*0.391*
6 Months	*-0.029*	*0.004*	*-0.033*	*0.084*
	0.018	*0.066*	*0.022*	*0.176*
1 Year	*-0.041****	*-0.034*	*-0.045**	*0.028*
	0.012	*0.047*	*0.023*	*0.178*
2 Year	*-0.054****	*-0.067*	*-0.025*	*0.009*
	0.019	*0.054*	*0.024*	*0.156*
3 Year	*-0.059****	*-0.034*	*-0.038**	*-0.015*
	0.015	*0.059*	*0.023*	*0.139*
4 Year	*-0.055****	*-0.050*	*-0.031*	*0.002*
	0.014	*0.040*	*0.019*	*0.121*
5 Year	*-0.059****	*-0.054*	*-0.048****	*-0.033*
	0.017	*0.041*	*0.015*	*0.150*
6 Year	*-0.063****	*-0.057*	*-0.051****	*-0.053*
	0.021	*0.042*	*0.012*	*0.154*
7 Year	*-0.025*	*-0.038*	*-0.009*	*-0.129*
	0.025	*0.038*	*0.009*	*0.129*
8 Year	*-0.064***	*-0.049**	*-0.049****	*-0.065*
	0.029	*0.027*	*0.009*	*0.115*
9 Year	*-0.066***	*-0.049****	*-0.054****	*-0.049*
	0.028	*0.019*	*0.009*	*0.116*
10 Year	*-0.064***	*-0.049****	*-0.057****	*-0.061*
	0.029	*0.016*	*0.009*	*0.106*
15 year	*-0.061***	*-0.058****	*-0.053****	*-0.058*
	0.030	*0.013*	*0.010*	*0.108*
20 Year	*-0.062***	*-0.058****	*-0.054****	*-0.058*
	0.030	*0.013*	*0.010*	*0.108*

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

Table 10 Impact of Timber Activity Within Buffer 1.5 km

Dependent Variable = Log(Sale Price) All Results are Individual Regressions	**Impact of Timber Activity Within Buffer** 1.5 Kilometer			
	Even Age		Uneven Age	
	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(9)	(10)	(11)	(12)
30 Days	-0.076***	-0.085	-0.020	0.044
	0.025	*0.128*	*0.048*	*0.261*
6 Months	-0.053***	-0.069	-0.004	0.038
	0.016	*0.056*	*0.010*	*0.076*
1 Year	-0.044***	-0.004	-0.020	0.018
	0.011	*0.033*	*0.018*	*0.084*
2 Year	-0.056***	-0.044*	-0.021	-0.007
	0.017	*0.025*	*0.022*	*0.113*
3 Year	-0.065***	-0.031	-0.034**	-0.040
	0.018	*0.031*	*0.017*	*0.069*
4 Year	-0.062***	-0.038	-0.046***	-0.044
	0.016	*0.028*	*0.017*	*0.067*
5 Year	-0.065***	-0.038	-0.059***	-0.061
	0.017	*0.045*	*0.013*	*0.085*
6 Year	-0.071***	-0.034	-0.057***	-0.071
	0.019	*0.036*	*0.011*	*0.095*
7 Year	-0.020	-0.035	-0.013	-0.084
	0.020	*0.035*	*0.013*	*0.084*
8 Year	-0.078***	-0.053	-0.054***	-0.063
	0.026	*0.058*	*0.016*	*0.052*
9 Year	-0.079***	-0.055	-0.053***	-0.049
	0.026	*0.054*	*0.015*	*0.045*
10 Year	-0.079***	-0.055	-0.053***	-0.043
	0.027	*0.056*	*0.015*	*0.051*
15 year	-0.075**	-0.053	-0.057***	-0.053
	0.029	*0.058*	*0.014*	*0.056*
20 Year	-0.076***	-0.052	-0.057***	-0.053
	0.029	*0.059*	*0.014*	*0.056*
Note: *p<0.1** p<0.05***p<0.01				

The impacts of uneven-age methods occurring within any of the buffers is also shown with a varying degree of statistical significant to be negative and persistent across time and distance. In similar fashion as the even-age results the less restrictive fixed effects results produced more statistically significant results. The more-restrictive fixed-effect model only produced four statistically significant results and those were for 8-20 years within 0.5km buffer. The less-restrictive model produced consistent estimates of approximately a 5% loss in home values when the estimate was statistically significant. The four stricter model estimates produced much larger negative results ranging between -15% to -16%. The loss to the median home sale price are $8,242 for model (4) and a loss of $23,540 to $24,988 for model (5) estimates. These large negative impacts are significant at a 99.9% confidence level.

The effect for the aggregate area cut model have varying statistically significant results for impacts of even-age methods across all distances and time. Tables 11 through 13 estimate the impact that an extra cut of 10 acres have on a home's sales price holding all the other variables constant. These models differ from the results presented in Tables 8through 10, because those models only estimated the effect of a single occurrence of a forest cut. The aggregate cut models estimate the impact that the total number of acres' cuts located inside the 0.5km, 1km and 1.5km buffer have on a home's sale price. These models measure the impacts of the intensity of the surrounding forest cutting activities. The prior models cannot discern the difference in the impacts to a home of an operation that cut one acre or another that cut 100 acres. To address that concern, I estimate the impacts of the intensity of cut using model (4) and (5) for 0.5 km, 1km, and 1.5km across the same amount of time as models (2) and (3).Table 11 Impact of an Extra 10 Acres of Timber Activity Within Buffer 0.5 km

Dependent Variable = Log(Sale Price)	**Impact of an Extra 10 Acres Of Timber Activity Within Buffer** 0.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)
30 Days	-0.02	-0.56	-0.059**	-0.023
	0.065	*0.819*	*0.026*	*0.023*
6 Months	-0.027	-0.161*	-0.035***	0.035
	0.019	*0.086*	*0.006*	*0.059*
1 Year	-0.039***	-0.066*	-0.023	0.013
	0.014	*0.035*	*0.014*	*0.059*
2 Year	-0.028***	-0.069**	-0.014	0.004
	0.003	*0.033*	*0.018*	*0.101*
3 Year	-0.015***	-0.057**	-0.021	-0.023
	0.004	*0.026*	*0.021*	*0.098*
4 Year	-0.013**	-0.039	-0 3	-0.049
	0.006	*0.025*	*1.90E-02*	*0.1*
5 Year	-0.014**	-0.046**	-0.009	-0.06
	0.007	*0.02*	*1.40E-02*	*8.00E-02*
6 Year	-0.019***	-0.065***	-0.014	-0.03
	0.007	*0.017*	*0.013*	*5.50E-02*
7 Year	-0.007	-0.02	-0.012	-0.049
	0.007	*0.02*	*1.20E-02*	*4.90E-02*
8 Year	-0.026***	-0.065***	-0.017	-0.035
	0.007	*0.022*	*1.10E-02*	*4.20E-02*
9 Year	-0.027***	-0.062**	-0.015	-0.027
	0.008	*0.025*	*0.01*	*0.031*
10 Year	-0.027***	-0.044*	-0.015	-0.028
	0.007	*0.026*	*0.009*	*0.031*
15 year	-0.029***	-0.033	-0.009	-0.029
	0.005	*0.03*	*0.006*	*0.029*
20 Year	-0.030***	-0.035	-0.009	-0.029
	0.005	*0.03*	*6.00E-03*	*0.029*
Note: *p<0.1** p<0.05***p<0.01				

Table 12 Impact of an Extra 10 Acres of Timber Activity Within Buffer 1 km

Dependent Variable = Log(Sale Price)	**Impact of an Extra 10 Acres of Timber Activity Within Buffer** 1 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(5)	(6)	(7)	(8)
30 Days	-0.081**	-0.124	-0.041*	-0.031
	0.03800	*0.088*	*0.023*	*0.034*
6 Months	-0.017	0.018	-0.013	0.131
	0.01100	*0.085*	*0.012*	*0.116*
1 Year	-0.017***	-0.022	-0.021*	0.065
	0.005	*0.027*	*0.012*	*0.073*
2 Year	-0.011***	-0.005	-0.003	0.005
	0.003	*0.015*	*0.01*	*0.059*
3 Year	-0.009***	0.001	-0.013	-0.018
	0.00300	*0.012*	*0.011*	*0.033*
4 Year	-0.009**	-0.002	-0.009	-0.021
	0.00400	*0.01*	*0.009*	*0.026*
5 Year	-0.009***	-0.004	-0.011**	-0.02
	0.00300	*0.007*	*0.005*	*0.023*
6 Year	-0.010***	-0.01	-0.011***	-0.016
	0.00300	*0.006*	*0.004*	*0.02*
7 Year	-3.00E-03	-0.006	-0.003	-0.016
	0.00300	*0.006*	*0.003*	*0.016*
8 Year	-0.010***	-0.010*	-0.012***	-0.017
	0.00300	*0.006*	*0.003*	*0.015*
9 Year	-0.011***	-0.011*	-0.011***	-0.012
	0.00300	*0.006*	*0.002*	*0.011*
10 Year	-0.009***	-0.007	-0.011***	-0.013
	0.00200	*0.006*	*0.002*	*0.011*
15 year	-0.010***	-0.005	-0.009***	-0.016
	0.00200	*0.006*	*0.002*	*0.01*
20 Year	-0.010***	-0.005	-0.009***	-0.016
	0.00200	*0.006*	*0.002*	*0.01*

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

Table 13 Impact of an Extra 10 Acres of Timber Activity Within Buffer 1.5 km

Dependent Variable = Log(Sale Price)	Impact of an extra 10 Acres of Timber Activity Within Buffer 1.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(9)	(10)	(11)	(12)
30 Days	-0.047***	-0.117	-0.037**	0.00600
	0.016	*0.083*	*0.016*	*0.036*
6 Months	-0.01	0.009	-0.006	-0.02200
	0.009	*0.028*	*0.004*	*0.08200*
1 Year	-0.010***	-0.01	-0.013***	-0.012
	0.003	*0.014*	*0.005*	*0.037*
2 Year	-0.007***	-0.003	-0.004	-0.014
	0.003	*0.012*	*0.006*	*0.019*
3 Year	-0.006**	0.001	-0.008	-0.01800
	0.003	*0.006*	*0.006*	*1.10E-02*
4 Year	-0.005***	0 2	-0.007	-0.019*
	0.001	*5.00E-03*	*0.005*	*0.01100*
5 Year	-0.005***	-0.001	-0.007**	-0.017**
	0.001	*4.00E-03*	*3.00E-03*	*0.00700*
6 Year	-0.006***	-0.004	-0.007**	-0.01400
	0.001	*0.004*	*3.00E-03*	*9.00E-03*
7 Year	-0.001	-0.003	-0.003	-0.00900
	0.001	*3.00E-03*	*3.00E-03*	*9.00E-03*
8 Year	-0.007***	-0.007**	-0.008***	-0.01200
	0.001	*3.00E-03*	*2.00E-03*	*0.00800*
9 Year	-0.008***	-0.007***	-0.007***	-0.00900
	0.001	*0.003*	*0.002*	*0.00600*
10 Year	-0.007***	-0.006*	-0.007***	-0.00800
	0.001	*0.003*	*0.002*	*0.00600*
15 year	-0.007***	-0.005*	-0.007***	-0.00900
	0.001	*0.003*	*0.002*	*0.00600*
20 Year	-0.007***	-0.005*	-0.007***	-0.00900
	0.001	*3.00E-03*	*0.002*	*0.00600*

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

Table 11 presents the estimated impacts of the total acreage cut within a 0.5km buffer for both even and uneven-age management. The estimated impacts for both even and uneven-age methods are negative, but statistically significant results are found in both even-age models and only model (4) for uneven-age methods. The estimates in Table 11 are the percentage change to a home's sales price per extra 10 acres of even-age forest cuts. Having a 10 acre even-age operation near the home within 30 days is only significant for the uneven-age method and it reduces the home's price by 5.6% (-$9,204). When the uneven-age results are statistically significant their estimated impacts are more negative than their significant even-age counterparts in the 0.5km buffer. Same as the prior models, the even-age estimates have far more statistically significant estimates in both fixed-effect models. The estimated impacts of the even-age methods vary between the two fixed-effect models. The less restrictive model produces losses ranging -1.5% (-$1,682) per 10 acres of even- age methods to -3% (-$4,995) loss. The more restrictive model produces estimates of -5%(-$8,242) to -6%(-$9,842). The fixed-effect models also differ on the length of the negative impacts. The less-restrictive model (4) shows the negative impacts increasing from the low of 6 years almost back to the most negative impact estimated at 20 years. Model (5) however, shows the impacts dwindle the further in time the 10-acre cut was.

The results for the 1km buffer regions in Table 12 show similar results for both even-age and uneven-age methods after the 1 year boundary. Both even and uneven results have significant results for the less-restrictive fixed-effects. The range of impacts for the 1km buffer ranges from -8%(-$12,993) to -0.9%%(-$1,514) for even-age and -4%(-$6,627) to -0.9%(-$1,514) for uneven-age methods. Starting at 5 Years the estimated impacts in the model (4) for even and uneven-age impacts are about the same negative impact for the remainder of the time periods.

The 1.5km buffer follows the same trend as the 1km buffer, but the impacts are smaller. Even-age impacts ranger from -4% %(-$6,627) to -.5%(-$843) and the uneven-age impacts fall between -3.7%(-$6,139) and -0.7%(-$1,179). When the even-age model (5) is significant starting at 0.1% or more, the estimates are the same as the less restrictive model (4). This only occurs once for the uneven-age methods results and the more restrictive impacts are estimated to be larger, in fact more than double the impact of model (4).

The following results were estimated on the subset of the data totaling 88,358 observations only located in rural Skagit, Thurston and Island counties. These three counties have majority of the home sales that were treated in all the buffer regions. The 0.5km buffer in the three counties have 59% of all the homes in the larger data set. The counties have 51% of the 1km buffer and 49% of the 1.5km buffer. These estimates are the impacts even and uneven-age forestry on rural homes. The more restrictive model requires an adequate number of observations within a block group and the time fixed effect control. This stricter requirement was not being met in the larger sample size, so the less restrictive models were used to estimate the following results. I also used models (2) and (4) because the prior results showed that the estimates produced similar direction of impact estimates, but had different magnitudes and varying significance due to the lack of observations. The summary statistics for the homes in this subset can be seen in table 14. The median home in this subset is $165,000, sits on 0.4 acres of land, has 1,394 ft^2, 3 bedrooms and is 26 years-old.

Table 14 Rural Skagit, Thurston, Island County Home Sales Summary Statistics

Rural Skagit, Thurston, Island County Home Sales Summary Statistics						
Statistic	N	Mean	St. Dev.	Min	Median	Max
SALEPRICE	88,358	200,317	152,239.800	1	165,000	3,950,000
ACRES	88,358	2.333	18.659	0.000	0.400	4,923.000
SqrFeet	88,358	1,393.526	793.628	0	1,394	31,232
Bedrooms	63,325	2.726	0.796	1	3	9
Age	88,358	289.927	669.632	-3,193	26	2,012
City	46,535	0.126	0.332	0	0	1
CPI1	46,470	184,059	111,335.300	51,734.250	154,753.000	2,732,004.000

Table 15 shows the impacts of the occurrence of both even and uneven-age methods across all buffer regions. These results show similar the same trend of both methods reducing home sale price across time and distance. Across all the buffer regions the 0.5km buffer has the most statistically significant result for even-age methods, while the 1 km buffer region produces the most significant results for the uneven-age cuts. The even-age methods show statistically significant impacts ranging -3%(-$5,516) to -7%(-$11,155) across all buffers and time. While the uneven-age methods have a significant range of -3.4%(-$5,993) to -15.8%(-$24,115) across all buffers and time as well.

Table 15 Impact of Timber Activity Within Buffer (Rural Subset)

Dependent Variable = Log(Sale Price)	Impact of Timber Activity Within Buffer (Rural Subset)					
	0.5 Kilometer		1 Kilometer		1.5 Kilometer	
	Even Age	Uneven Age	Even Age	Uneven Age	Even Age	Uneven Age
All Results are Individual Regressions	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)	(5)	(6)
30 Days	-0.297*	-0.277**	-0.03300	-0.158***	-0.079***	-0.120***
	0.172	*0.120*	*0.026*	*0.049*	*0.024*	*0.032*
6 Months	-0.015	0.01400	0.00200	-0.03200	-0.024	-0.023
	0.037	*0.068*	*0.030*	*0.025*	*0.018*	*0.018*
1 Year	-0.002	0.02700	-0 30	-0.045***	0.008	-0.01
	0.043	*0.038*	*0.028*	*0.017*	*0.020*	*0.011*
2 Year	-0.016	-0.03600	-0.00600	-0.045**	-0.006	-0.011
	0.024	*0.040*	*0.030*	*0.022*	*0.022*	*0.013*
3 Year	-0.02	-0.046*	-0.01900	-0.056***	-0.024	-0.026**
	0.025	*0.025*	*0.024*	*0.019*	*0.023*	*0.013*
4 Year	-0.021	-0.026*	-0.02100	-0.030**	-0.019	-0.018*
	0.024	*0.015*	*0.025*	*0.013*	*0.027*	*0.010*
5 Year	-0.025	-0.040***	-0.02300	-0.034***	-0.006	-0.025***
	0.023	*0.011*	*0.023*	*0.011*	*0.027*	*0.004*
6 Year	-0.030**	-0.037***	-0.026*	-0.038***	-0.011	-0.021***
	0.013	*0.013*	*0.015*	*0.014*	*0.021*	*0.006*
7 Year	-0.01	-0.01800	-0.01600	-0.01300	-0.021	-0.013
	0.010	*0.018*	*0.016*	*0.013*	*0.021*	*0.013*
8 Year	-0.051***	-0.042*	-0.02700	-0.029*	-0.018	-0.015
	0.013	*0.024*	*0.021*	*0.015*	*0.017*	*0.020*
9 Year	-0.055***	-0.03300	-0.035*	-0.038*	-0.022	-0.016
	0.011	*0.022*	*0.019*	*0.020*	*0.018*	*0.024*
10 Year	-0.058***	-0.049**	-0.036*	-0.049***	-0.027*	-0.017
	0.015	*0.019*	*0.020*	*0.018*	*0.016*	*0.024*
15 year	-0.066***	-0.049**	-0.02800	-0.02900	-0.019	-0.005
	0.013	*0.019*	*0.018*	*0.028*	*0.015*	*0.036*
20 Year	-0.067***	-0.052***	-0.030*	-0.031	-0.02	-0.004
	0.014	*0.019*	*0.018*	*0.029*	*0.014*	*0.037*
Note: *p<0.1** p<0.05***p<0.01						

Table 16 Impact of an extra 10 Acres of Timber Activity Within Buffer (Rural Subset)

Dependent Variable = Log(Sale Price)	Impact of an extra 10 Acres of Timber Activity Within Buffer (Rural Subset)					
	0.5 Kilometer		1 Kilometer		1.5 Kilometer	
	Even Age	Uneven Age	Even Age	Uneven Age	Even Age	Uneven Age
All Results are Individual Regressions	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)	(5)	(6)
30 Days	-0.678*	-0.065	-0.128	-0.064**	-0.058***	-0.052***
	0.378	*0.056*	*0.087*	0.027	0.016	0.010
6 Months	-0.009	-0.011	0.006	-0.012	0.004	-0.002
	0.023	*0.019*	*0.012*	0.010	0.012	0.006
1 Year	-0.024	-0.029***	-0.002	-0.022***	-0.001	-0.010***
	0.017	*0.007*	*0.003*	0.008	0.004	0.003
2 Year	-0.016	-0.040**	0.002	-0.009	0.003	-0.005
	0.014	*0.015*	*0.002*	0.009	0.004	0.005
3 Year	-0.008	-0.045***	0	-0.014	0	-0.008*
	0.015	*0.015*	*0.004*	0.010	0.003	0.004
4 Year	-0.010	-0.013	-0.001	-0.011	0	-0.007
	0.018	*0.017*	*0.003*	0.008	0.001	0.004
5 Year	-0.013	-0.017	-0.002	-0.011***	0	-0.007***
	0.016	*0.012*	*0.003*	0.004	0.001	0.003
6 Year	-0.018	-0.024	-0.005*	-0.010**	-0.002*	-0.006**
	0.011	*0.016*	*0.003*	0.004	0.001	0.003
7 Year	-0.010	-0.011	-0.003	-0.002	-0.001	-0.002
	0.010	*0.011*	*0.003*	0.002	0.001	0.002
8 Year	-0.025***	-0.035***	-0.005	-0.012***	-0.003***	-0.007***
	0.008	*0.013*	*0.003*	0.002	0.001	0.002
9 Year	-0.026***	-0.040***	-0.006*	-0.012***	-0.004***	-0.006**
	0.009	*0.013*	*0.003*	0.003	0.001	0.002
10 Year	-0.024***	-0.042***	-0.005*	-0.012***	-0.003***	-0.006***
	0.005	*0.013*	*0.003*	0.002	0.001	0.002
15 year	-0.028***	-0.035***	-0.006**	-0.011***	-0.004***	-0.006**
	0.007	*0.006*	*0.003*	0.003	0.001	0.002
20 Year	-0.029***	-0.034***	-0.006*	-0.011***	-0.003***	-0.006**
	0.007	*0.006*	*0.003*	0.003	0.001	0.002
Note: *p<0.1** p<0.05***p<0.01						

Table 16 is the subset results for an extra ten acres of forest cut with either even or uneven methods. The results show statistically significant negative results for both methods across all buffers. As the forest cuts are further away from the home, the smaller the impact on the home's sale price. An interesting result is that the uneven-age impacts are more negative than the even-age impacts. In the 0.5km buffer the even-age has reduces a home price by ~2.5% and the uneven-age methods reduce the price by ~4%. The impacts dwindle to ~.06% in the 1km buffer and .03% in the 1.5km for even-age. The impacts reduce for uneven-age as well, but are still larger than their even-age equivalents. At 1km the practice reduces the price by ~1.1% and in the 1.5km buffer the home price falls by ~.06%.

4.5 Discussion and Conclusion

The results from all the models show broadly that people do not prefer forest activity near their homes. This negative preference can be seen across all the even-age and uneven-age results. In the results there are persistently negative and statistically significant impacts shown. None of the regression models have a single statistically significant positive impact associated with either even-age or uneven-age methods This long-lasting effect is seen in both methods and models, but the magnitudes associated with the methods differ. While there are some impacts that show negative impacts for uneven-age methods majority of the impacts for the more restrictive fixed effects models (3) and (5) have large standard errors producing confidence intervals that do not provide any significant explanation of the impacts of the uneven-age methods. This difference in impacts shows that people value the even-age methods negatively with reasonably certainty and that people potentially are indifferent to the uneven-age methods. When the impacts in the full data set models are statistically significant for uneven-age models the estimated impacts are always within the same magnitude of impacts as even-age. This trend of similar or less then magnitude of impacts for uneven-age methods persist for the occurrence results in the rural subset results, but the per ten acre results depart from the findings of the other results. The uneven-age impacts are always larger than the even-age impacts. Even with this contradiction all the models used reflect the findings of the past literature for peoples' perceptions and WTP towards forest practices and even-age methods.

I believe that the negative impacts for the timber activities have a few explanations. The first is that there is a well-documented perception by the public that forest cutting is unaesthetic (Palmer et al. 2005, Ribe and Matteson 2002; Bliss 2000). People who choose to buy homes near forests pay premiums to do so. This is well documented in studies by Czembrowski and Kronenberg (2016), Gómez-Baggethun and Barton (2013), and Melichar and Kaprová (2013). Reducing the surrounding forest near a home, in turn reduces a part of the reason the home buyers bought the home initially.

The second explanation is that timber operations require many workers, machines and are not fast endeavors. The standard amount of time permitted to cut a section of forest in the forest permit data set was two years, regardless of what method used. These permits can also be extended past the two-year mark, allowing for more operations on the specific tree stand. These factors compile into a potential reason for the persisting negative impact on home sales.

The second model is the first attempt to economically measure the impact of the intensity of cutting the surrounding forests of a home. These results as discussed earlier show that there are significant negative impacts across time and distance for even-age methods. Uneven-age methods in general show estimated negative impacts, but with only limited significant estimates, it can be reasoned that people are indifferent to these methods and at worst show negative views to the methods. In general, these models show that the further away the forest practices are the less they impact the homes sales price. This can be seen by the reduction of the impacts between 0.5km, 1km, and the 1.5km models. Intuitively this makes sense, if there was 10 acres cut within 0.5km of the house this would be drastic and noticeable. Aside from the major loss in forest surrounding the home the operations would be close to the home for some time.

When looking specifically at the comparison of even-age and uneven-age estimates for model 2 there are a few similarities. Both methods show negative impacts to home prices across all time periods in 0.5km, 1km and the 1.5km buffers. No estimate in either of the models showed increases to a home's sales price. These results do not reflect the estimates found in the natural view and open space literature in economics. Research by Cavailhès et al. 2009 and Baranzini and Schaerer 2011 and other papers show positive impacts for areas with fewer trees. This thinning of the forest produces clear views of the surrounding environment which has been shown to produce some positive impacts (also see Benson et al. 1998, Patterson and Bolye 2002, Sander and Polasky 2010). The specified models did control for the potential types of views that a home had, but the negative impacts associated with the forest cutting operation could be over powering any beneficial view gained by the home.

The estimated impacts are seen to have statistically significant negative impacts that persist for many years. One major explanation of the persistent negative impacts is the loss in job opportunities due to past forest operations. Tree stands take a considerably long time to grow back to be harvested. It is possible that the negative impacts that are persistent are showing the impact that the loss of timber job opportunities due to the reduction of forests from past logging. The reduction in job opportunities reduces the regional economy in turn lowering home prices.

I estimated models for 0.5km, 1km, and 1.5km that assessed the impacts from the occurrence of timber activities along with the amount of forest cut for each added year. The first model attempted to estimate the impact that having a forest practice within the designated buffers had on a home's sales price. The second model quantified the impact of forest acres cut over time on home prices. The results for 0.5km 1km, and 1.5km for these two models produced statistically significant negative impacts across time and distance. I also estimated another model like the aggregate cut models, with the estimated board-feet extracted data provided. These results were inconsistent, and I believe it is due to how the data for board feet extracted were estimates produced by the foresters rather than actual extraction numbers. In addition to these models, 2km and 3km buffers were drawn and attempted. The sheer amount of data for these two buffer levels had repeated GIS errors and were set aside due to computational limitations.

All in all, the outcome of the results support empirical results for the multiple perception studies of clearcutting by Palmer et al. (2005), Ribe and Matteson (2002) and Bliss (2000), people do not value forest cutting. In accord with Kim and Johnson (2002) the impacts were statistically significant and large. The impacts of these practices demonstrate that the public does care about the forest cutting method employed. With a statistically significant negative results for uneven-age and even-age methods it is reasonable to conclude that the public sees forest cutting negatively. The impact of these forest practices has never been the explicit focus of any study to date. The lack of evaluation of the impacts of the forest practices mean forest managers and WSDNR have been operating and permitting forest practices without knowledge of their full impact on the social welfare. The long-lasting impacts and the negative impacts of large acre cuts near homes shows the economic impacts of these forest practices need to be considered. The NTV that is lost due to the forest practices in the worst case outweigh the TV gained by cutting the forest. Without considering the cost as well as the benefit of forest practices, economically inefficient forest cuts will occur. Economically efficient forest management decisions will consider the benefits gained from the TV of the forest, while comparing loss in NTV from the surrounding real estate market at a minimum.

This paper takes a necessary step forward in the forestry economics literature. There is a substantial need to evaluate the varying forest cutting methods used in forests, even-age and uneven-age. Future research should attempt to do similar evaluations, because the estimations reported here are based off the utility and preferences of the residents of ten western Washington counties. The preferences of western Washington residents may not match those preferences of other areas, meaning the magnitude and potential directions of the estimates of the impacts would not be applicable to other areas. Further research should look to see the varying impacts of different forest types, the data set used in this research did not have information on the types of trees or forest cut, only methods. Along with forest tree type, this study could only measure the over-arching forest practices of uneven and even-age methods. With a more detailed data set on styles of even or uneven cutting methods used the estimates for forester and forest managers can be improved. This paper did not employ view shed analysis for homes to add, what I believe is an important variable. Kim and Johnson (2002) employed this technique and it showed negative impacts. Another potential addition would be simple categorical controls for forests characteristics in the models.

V POLICY, PROBLEMS AND FURTHER WORK

5.1 Policy Implications

In 2013 Washington state legislature amended the Washington forest practice rules and created the Adaptive Management Program (AMP) (WSDNR 2013b). The mission of the AMP "affect change when it is necessary or advisable to adjust rules and guidance for aquatic resources to achieve the goals of the Forest Practices Act or other goals identified by the Board . . . , which are aimed at ensuring that forest practices, either singly or cumulatively, will not significantly impair the capacity of aquatic habitat. . ." (WSDNR 2013a). The AMP has a diverse group of participants that involves private forests owners, Departments of Fish and Wildlife and Ecology, and Industrial private timber owners to name a few (WSDNR 2013a). This program emphasizes the use of "relevant science from all credible sources including peer-reviewed government and university research…" to inform policy and to even amend forest practice rules to produce more efficient outcomes (WSDNR 2013a).

I believe that this paper fits into this organization framework to help inform policy creators and forest managers in western Washington. This paper is an evaluation of the forest practice policies and rules implemented by the WSDNR and, in turn, under the regulatory evaluation of the AMP. This paper demonstrates statistically significant empirical results of the rules and guidelines of how cutting the WSNDR governed forests are impacting the regional economy of western Washington. The AMP was created to meet what the Forest Practice Board says current research "lacks the certainty to answer all the pertinent questions associated with the forest practices rules" (WSNDR 2013a). While this paper was not commissioned by the WSDNR or the Cooperative Monitoring Evaluation and Research Committee (CMER) used by the AMP, it provides the new research to evaluate forest practices.

The results of this paper show that regardless of intensity and method use, timber practices near homes have negative impacts. The AMP and the CMER should use these findings to aid the economic feasibility of permitted forest cuts. The results of this paper do not argue the halting of timber activities in Washington State. The results show empirically what prior research has demonstrated, people do not like timber practices. This research should add another consideration to the WSNDR permit approval process. The research shows that forest practice near homes creates the greatest loss to home owners. The research suggests that there may be an "optimal" distance from a home, where the impact's negative impact is less than the TV of the forest cut.

5.2 Problems

This paper omits the major urban areas of the study are due to lack of data in those counties. Due to the lack of observations, I believe that some of the estimations could have been different. For example, urban forests are usually closer to homes, meaning more observations in the 0.5km buffer regions. Also, people who live near urban forests pay a premium for these environmental amenities, and by cutting these forests I believe the impacts could have been large in magnitude.

Aside from better and more detailed forest practice information as discussed earlier, majority of the problems in this study had to do with data management. Producing the data sets used in this research required spatially intersecting the geocoded home sales and the forest practice polygons that were later aggregated and cleaned in the R statistical software. The process of intersecting is in relational database terms a one-to-many spatial join of attribute tables. For every home sale, a row was created for each individual forest cut that was found to intersect within the different buffer regions. Since there is a one to many join the home sales data set will become larger than the original, but this problem is minor when working with small buffer distance. An example of this is the 0.5km buffer would produce five rows for one home sale, but in the 2km buffers a home sale could easily have 15 rows produced from one sale. Due to this massive one-to-many join being replicated for every buffer distance, the raw intersect data was almost 1.5 terabytes in size. I would like to note that due to major GIS computational limits and crashing the 2km buffers data included were incomplete. The 2km files were fully processed, but when checking the data before processing the data for analysis the total size of the 2km cuts was hundreds of gigabytes less than the 1km files. As the buffer regions expand more forest cuts are being intersected with the home sales and a larger buffer zones includes all the previous forest cuts. By this logic the data files for large cuts must be greater in size, for the 2km data to be smaller means there were errors due to the continual crashes and memory limits being met.

The process of producing a complete 2km data process was not achieved for this thesis. Considering the 2km failures, the 3km buffers were never attempted.

5.3 Further Work

Further studies are needed to improve the understanding of the full economic impact that forest practice have on the economy. The use of GIS is pivotal in the study of this topic and further GIS implementation can add further detail to the studies. Using methods similar to Kim and Johnson (2002) and Walls et al. (2015), using view shed analysis can add greater detail to the estimates. The forest practice data did not provide characteristic of forest make up and forest coverage in the tree stands. This information would be ideal measure when trying to assess the impact of forest cutting near homes. Remote sensing data can add these characteristics along with other data for the forest cuts and home sales. This data is common for GIS software and it can add more specificity to the analysis. A final recommendation is for greater temporal specific studies. This research shows persistent negative impacts; in some model's estimations, these impacts begin to decrease. The study here capped the time analysis at ten years and for the majority used annual intervals. Future studies should look at the impacts for longer durations of time.

Aside from the addition of data and new methods to the analysis, further research should focus on more specific geographic areas. The impacts of a large regional area may not accurately estimate the impacts of smaller areas like counties or towns. This study’s broader analysis is most applicable for policy analysis for regionals management, but local towns and county government need to assess their own citizens' preferences for timber activities. The impacts estimated here may not be reflective of how they truly perceive these practices. For example, smaller population counties like Wahkiakum County and has many forest cuts may have estimates that are smaller in magnitude than estimated here.

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APPENDIXES

Table 17 Impact of Timber Activity within Buffer 0.5 km

Dependent Variable = Log(Sale Price)	**Impact of Timber Activity Within Buffer** 0.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)
30 Days	-0.075	-0.286	-0.058	-0.094
	0.088	*0.380*	*0.046*	*0.092*
6 Months	-0.033**	-0.118	0.005	0.213
	0.015	*0.130*	*0.019*	*0.179*
1 Year	-0.052**	-0.053	0.009	0.141
	0.023	*0.072*	*0.049*	*0.150*
2 Year	-0.049***	-0.083	-0.003	0.055
	0.014	*0.078*	*0.036*	*0.151*
3 Year	-0.048***	-0.025	-0.015	0.005
	0.011	*0.059*	*0.035*	*0.145*
4 Year	-0.047**	-0.054	0.002	-0.034
	0.019	*0.070*	*0.031*	*0.118*
5 Year	-0.050***	-0.038	-0.022	-0.103
	0.019	*0.073*	*0.019*	*0.106*
6 Year	-0.058**	-0.075	-0.029*	-0.140
	0.023	*0.072*	*0.015*	*0.088*
7 Year	-0.025	-0.096*	-0.019	-0.065
	0.025	*0.058*	*0.019*	*0.065*
8 Year	-0.067**	-0.084*	-0.041**	-0.160***
	0.026	*0.043*	*0.018*	*0.051*
9 Year	-0.064**	-0.078***	-0.037**	-0.159***
	0.025	*0.029*	*0.018*	*0.049*
10 Year	-0.064**	-0.069***	-0.049***	-0.156***
	0.029	*0.025*	*0.018*	*0.046*
15 year	-0.067**	-0.063**	-0.056**	-0.153***
	0.030	*0.026*	*0.022*	*0.058*
20 Year	-0.068**	-0.063**	-0.059***	-0.152**
	0.030	*0.026*	*0.022*	*0.059*

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

Table 18 Impact of Timber Activity within Buffer 1 km

Dependent Variable = Log(Sale Price)	**Impact of Timber Activity Within Buffer** 1 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(5)	(6)	(7)	(8)
30 Days	-0.073**	-0.158	-0.048	-0.074
	0.034	*0.282*	*0.072*	*0.391*
6 Months	*-0.029*	*0.004*	*-0.033*	*0.084*
	0.018	*0.066*	*0.022*	*0.176*
1 Year	*-0.041****	*-0.034*	*-0.045**	*0.028*
	0.012	*0.047*	*0.023*	*0.178*
2 Year	*-0.054****	*-0.067*	*-0.025*	*0.009*
	0.019	*0.054*	*0.024*	*0.156*
3 Year	*-0.059****	*-0.034*	*-0.038**	*-0.015*
	0.015	*0.059*	*0.023*	*0.139*
4 Year	*-0.055****	*-0.050*	*-0.031*	*0.002*
	0.014	*0.040*	*0.019*	*0.121*
5 Year	*-0.059****	*-0.054*	*-0.048****	*-0.033*
	0.017	*0.041*	*0.015*	*0.150*
6 Year	*-0.063****	*-0.057*	*-0.051****	*-0.053*
	0.021	*0.042*	*0.012*	*0.154*
7 Year	*-0.025*	*-0.038*	*-0.009*	*-0.129*
	0.025	*0.038*	*0.009*	*0.129*
8 Year	*-0.064***	*-0.049**	*-0.049****	*-0.065*
	0.029	*0.027*	*0.009*	*0.115*
9 Year	*-0.066***	*-0.049****	*-0.054****	*-0.049*
	0.028	*0.019*	*0.009*	*0.116*
10 Year	*-0.064***	*-0.049****	*-0.057****	*-0.061*
	0.029	*0.016*	*0.009*	*0.106*
15 year	*-0.061***	*-0.058****	*-0.053****	*-0.058*
	0.030	*0.013*	*0.010*	*0.108*
20 Year	*-0.062***	*-0.058****	*-0.054****	*-0.058*
	0.030	*0.013*	*0.010*	*0.108*

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

Table 19 Impact of Timber Activity Within Buffer 1.5 km

Dependent Variable = Log(Sale Price) All Results are Individual Regressions	**Impact of Timber Activity Within Buffer** 1.5 Kilometer			
	Even Age		Uneven Age	
	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(9)	(10)	(11)	(12)
30 Days	-0.076***	-0.085	-0.020	0.044
	0.025	*0.128*	*0.048*	*0.261*
6 Months	-0.053***	-0.069	-0.004	0.038
	0.016	*0.056*	*0.010*	*0.076*
1 Year	-0.044***	-0.004	-0.020	0.018
	0.011	*0.033*	*0.018*	*0.084*
2 Year	-0.056***	-0.044*	-0.021	-0.007
	0.017	*0.025*	*0.022*	*0.113*
3 Year	-0.065***	-0.031	-0.034**	-0.040
	0.018	*0.031*	*0.017*	*0.069*
4 Year	-0.062***	-0.038	-0.046***	-0.044
	0.016	*0.028*	*0.017*	*0.067*
5 Year	-0.065***	-0.038	-0.059***	-0.061
	0.017	*0.045*	*0.013*	*0.085*
6 Year	-0.071***	-0.034	-0.057***	-0.071
	0.019	*0.036*	*0.011*	*0.095*
7 Year	-0.020	-0.035	-0.013	-0.084
	0.020	*0.035*	*0.013*	*0.084*
8 Year	-0.078***	-0.053	-0.054***	-0.063
	0.026	*0.058*	*0.016*	*0.052*
9 Year	-0.079***	-0.055	-0.053***	-0.049
	0.026	*0.054*	*0.015*	*0.045*
10 Year	-0.079***	-0.055	-0.053***	-0.043
	0.027	*0.056*	*0.015*	*0.051*
15 year	-0.075**	-0.053	-0.057***	-0.053
	0.029	*0.058*	*0.014*	*0.056*
20 Year	-0.076***	-0.052	-0.057***	-0.053
	0.029	*0.059*	*0.014*	*0.056*

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

Table 20 Impact of an Extra 10 Acres of Timber Activity Within Buffer 0.5 km

Dependent Variable = Log(Sale Price)	Impact of an Extra 10 Acres Of Timber Activity Within Buffer 0.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)
30 Days	-0.02	-0.56	-0.059**	-0.023
	0.065	*0.819*	*0.026*	*0.023*
6 Months	-0.027	-0.161*	-0.035***	0.035
	0.019	*0.086*	*0.006*	*0.059*
1 Year	-0.039***	-0.066*	-0.023	0.013
	0.014	*0.035*	*0.014*	*0.059*
2 Year	-0.028***	-0.069**	-0.014	0.004
	0.003	*0.033*	*0.018*	*0.101*
3 Year	-0.015***	-0.057**	-0.021	-0.023
	0.004	*0.026*	*0.021*	*0.098*
4 Year	-0.013**	-0.039	-0 3	-0.049
	0.006	*0.025*	*1.90E-02*	*0.1*
5 Year	-0.014**	-0.046**	-0.009	-0.06
	0.007	*0.02*	*1.40E-02*	*8.00E-02*
6 Year	-0.019***	-0.065***	-0.014	-0.03
	0.007	*0.017*	*0.013*	*5.50E-02*
7 Year	-0.007	-0.02	-0.012	-0.049
	0.007	*0.02*	*1.20E-02*	*4.90E-02*
8 Year	-0.026***	-0.065***	-0.017	-0.035
	0.007	*0.022*	*1.10E-02*	*4.20E-02*
9 Year	-0.027***	-0.062**	-0.015	-0.027
	0.008	*0.025*	*0.01*	*0.031*
10 Year	-0.027***	-0.044*	-0.015	-0.028
	0.007	*0.026*	*0.009*	*0.031*
15 year	-0.029***	-0.033	-0.009	-0.029
	0.005	*0.03*	*0.006*	*0.029*
20 Year	-0.030***	-0.035	-0.009	-0.029
	0.005	*0.03*	*6.00E-03*	*0.029*

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

Table 21 Impact of an Extra 10 Acres of Timber Activity Within Buffer 1 km

Dependent Variable = Log(Sale Price)	Impact of an Extra 10 Acres of Timber Activity Within Buffer 1 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(5)	(6)	(7)	(8)
30 Days	-0.081**	-0.124	-0.041*	-0.031
	0.03800	*0.088*	*0.023*	*0.034*
6 Months	-0.017	0.018	-0.013	0.131
	0.01100	*0.085*	*0.012*	*0.116*
1 Year	-0.017***	-0.022	-0.021*	0.065
	0.005	*0.027*	*0.012*	*0.073*
2 Year	-0.011***	-0.005	-0.003	0.005
	0.003	*0.015*	*0.01*	*0.059*
3 Year	-0.009***	0.001	-0.013	-0.018
	0.00300	*0.012*	*0.011*	*0.033*
4 Year	-0.009**	-0.002	-0.009	-0.021
	0.00400	*0.01*	*0.009*	*0.026*
5 Year	-0.009***	-0.004	-0.011**	-0.02
	0.00300	*0.007*	*0.005*	*0.023*
6 Year	-0.010***	-0.01	-0.011***	-0.016
	0.00300	*0.006*	*0.004*	*0.02*
7 Year	-3.00E-03	-0.006	-0.003	-0.016
	0.00300	*0.006*	*0.003*	*0.016*
8 Year	-0.010***	-0.010*	-0.012***	-0.017
	0.00300	*0.006*	*0.003*	*0.015*
9 Year	-0.011***	-0.011*	-0.011***	-0.012
	0.00300	*0.006*	*0.002*	*0.011*
10 Year	-0.009***	-0.007	-0.011***	-0.013
	0.00200	*0.006*	*0.002*	*0.011*
15 year	-0.010***	-0.005	-0.009***	-0.016
	0.00200	*0.006*	*0.002*	*0.01*
20 Year	-0.010***	-0.005	-0.009***	-0.016
	0.00200	*0.006*	*0.002*	*0.01*

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

Table 22 Impact of an Extra 10 Acres of Timber Activity Within Buffer 1.5 km

Dependent Variable = Log(Sale Price)	**Impact of an extra 10 Acres of Timber Activity Within Buffer** 1.5 Kilometer			
	Even Age		Uneven Age	
All Results are Individual Regressions	(BG + Qu)	(Qu * BG)	(BG + Qu)	(Qu * BG)
Time Sold After Timber Activity	(9)	(10)	(11)	(12)
30 Days	-0.047***	-0.117	-0.037**	0.00600
	0.016	*0.083*	*0.016*	*0.036*
6 Months	-0.01	0.009	-0.006	-0.02200
	0.009	*0.028*	*0.004*	*0.08200*
1 Year	-0.010***	-0.01	-0.013***	-0.012
	0.003	*0.014*	*0.005*	*0.037*
2 Year	-0.007***	-0.003	-0.004	-0.014
	0.003	*0.012*	*0.006*	*0.019*
3 Year	-0.006**	0.001	-0.008	-0.01800
	0.003	*0.006*	*0.006*	*1.10E-02*
4 Year	-0.005***	0 2	-0.007	-0.019*
	0.001	*5.00E-03*	*0.005*	*0.01100*
5 Year	-0.005***	-0.001	-0.007**	-0.017**
	0.001	*4.00E-03*	*3.00E-03*	*0.00700*
6 Year	-0.006***	-0.004	-0.007**	-0.01400
	0.001	*0.004*	*3.00E-03*	*9.00E-03*
7 Year	-0.001	-0.003	-0.003	-0.00900
	0.001	*3.00E-03*	*3.00E-03*	*9.00E-03*
8 Year	-0.007***	-0.007**	-0.008***	-0.01200
	0.001	*3.00E-03*	*2.00E-03*	*0.00800*
9 Year	-0.008***	-0.007***	-0.007***	-0.00900
	0.001	*0.003*	*0.002*	*0.00600*
10 Year	-0.007***	-0.006*	-0.007***	-0.00800
	0.001	*0.003*	*0.002*	*0.00600*
15 year	-0.007***	-0.005*	-0.007***	-0.00900
	0.001	*0.003*	*0.002*	*0.00600*
20 Year	-0.007***	-0.005*	-0.007***	-0.00900
	0.001	*3.00E-03*	*0.002*	*0.00600*

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

Table 23 Rural Skagit, Thurston, Island County Home Sales Summary Statistics

Rural Skagit, Thurston, Island County Home Sales Summary Statistics						
Statistic	N	Mean	St. Dev.	Min	Median	Max
SALEPRICE	88,358	200,317	152,239.800	1	165,000	3,950,000
ACRES	88,358	2.333	18.659	0.000	0.400	4,923.000
SqrFeet	88,358	1,393.526	793.628	0	1,394	31,232
Bedrooms	63,325	2.726	0.796	1	3	9
Age	88,358	289.927	669.632	-3,193	26	2,012
City	46,535	0.126	0.332	0	0	1
CPI1	46,470	184,059	111,335.300	51,734.250	154,753.000	2,732,004.000

Table 24 Impact of Timber Activity Within Buffer (Rural Subset)

Dependent Variable = Log(Sale Price)	Impact of Timber Activity Within Buffer (Rural Subset)					
	0.5 Kilometer		1 Kilometer		1.5 Kilometer	
	Even Age	Uneven Age	Even Age	Uneven Age	Even Age	Uneven Age
All Results are Individual Regressions	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)	(5)	(6)
30 Days	-0.297*	-0.277**	-0.03300	-0.158***	-0.079***	-0.120***
	0.172	*0.120*	*0.026*	*0.049*	*0.024*	*0.032*
6 Months	-0.015	0.01400	0.00200	-0.03200	-0.024	-0.023
	0.037	*0.068*	*0.030*	*0.025*	*0.018*	*0.018*
1 Year	-0.002	0.02700	-0 30	-0.045***	0.008	-0.01
	0.043	*0.038*	*0.028*	*0.017*	*0.020*	*0.011*
2 Year	-0.016	-0.03600	-0.00600	-0.045**	-0.006	-0.011
	0.024	*0.040*	*0.030*	*0.022*	*0.022*	*0.013*
3 Year	-0.02	-0.046*	-0.01900	-0.056***	-0.024	-0.026**
	0.025	*0.025*	*0.024*	*0.019*	*0.023*	*0.013*
4 Year	-0.021	-0.026*	-0.02100	-0.030**	-0.019	-0.018*
	0.024	*0.015*	*0.025*	*0.013*	*0.027*	*0.010*
5 Year	-0.025	-0.040***	-0.02300	-0.034***	-0.006	-0.025***
	0.023	*0.011*	*0.023*	*0.011*	*0.027*	*0.004*
6 Year	-0.030**	-0.037***	-0.026*	-0.038***	-0.011	-0.021***
	0.013	*0.013*	*0.015*	*0.014*	*0.021*	*0.006*
7 Year	-0.01	-0.01800	-0.01600	-0.01300	-0.021	-0.013
	0.010	*0.018*	*0.016*	*0.013*	*0.021*	*0.013*
8 Year	-0.051***	-0.042*	-0.02700	-0.029*	-0.018	-0.015
	0.013	*0.024*	*0.021*	*0.015*	*0.017*	*0.020*
9 Year	-0.055***	-0.03300	-0.035*	-0.038*	-0.022	-0.016
	0.011	*0.022*	*0.019*	*0.020*	*0.018*	*0.024*
10 Year	-0.058***	-0.049**	-0.036*	-0.049***	-0.027*	-0.017
	0.015	*0.019*	*0.020*	*0.018*	*0.016*	*0.024*
15 year	-0.066***	-0.049**	-0.02800	-0.02900	-0.019	-0.005
	0.013	*0.019*	*0.018*	*0.028*	*0.015*	*0.036*
20 Year	-0.067***	-0.052***	-0.030*	-0.031	-0.02	-0.004
	0.014	*0.019*	*0.018*	*0.029*	*0.014*	*0.037*

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

Table 25 Impact of an extra 10 Acres of Timber Activity Within Buffer (Rural Subset)

Dependent Variable = Log(Sale Price)	Impact of an extra 10 Acres of Timber Activity Within Buffer (Rural Subset)					
	0.5 Kilometer		1 Kilometer		1.5 Kilometer	
	Even Age	Uneven Age	Even Age	Uneven Age	Even Age	Uneven Age
All Results are Individual Regressions	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)	(BG + Qu)
Time Sold After Timber Activity	(1)	(2)	(3)	(4)	(5)	(6)
30 Days	-0.678*	-0.065	-0.128	-0.064**	-0.058***	-0.052***
	0.378	*0.056*	*0.087*	0.027	0.016	0.010
6 Months	-0.009	-0.011	0.006	-0.012	0.004	-0.002
	0.023	*0.019*	*0.012*	0.010	0.012	0.006
1 Year	-0.024	-0.029***	-0.002	-0.022***	-0.001	-0.010***
	0.017	*0.007*	*0.003*	0.008	0.004	0.003
2 Year	-0.016	-0.040**	0.002	-0.009	0.003	-0.005
	0.014	*0.015*	*0.002*	0.009	0.004	0.005
3 Year	-0.008	-0.045***	0	-0.014	0	-0.008*
	0.015	*0.015*	*0.004*	0.010	0.003	0.004
4 Year	-0.010	-0.013	-0.001	-0.011	0	-0.007
	0.018	*0.017*	*0.003*	0.008	0.001	0.004
5 Year	-0.013	-0.017	-0.002	-0.011***	0	-0.007***
	0.016	*0.012*	*0.003*	0.004	0.001	0.003
6 Year	-0.018	-0.024	-0.005*	-0.010**	-0.002*	-0.006**
	0.011	*0.016*	*0.003*	0.004	0.001	0.003
7 Year	-0.010	-0.011	-0.003	-0.002	-0.001	-0.002
	0.010	*0.011*	*0.003*	0.002	0.001	0.002
8 Year	-0.025***	-0.035***	-0.005	-0.012***	-0.003***	-0.007***
	0.008	*0.013*	*0.003*	0.002	0.001	0.002
9 Year	-0.026***	-0.040***	-0.006*	-0.012***	-0.004***	-0.006**
	0.009	*0.013*	*0.003*	0.003	0.001	0.002
10 Year	-0.024***	-0.042***	-0.005*	-0.012***	-0.003***	-0.006***
	0.005	*0.013*	*0.003*	0.002	0.001	0.002
15 year	-0.028***	-0.035***	-0.006**	-0.011***	-0.004***	-0.006**
	0.007	*0.006*	*0.003*	0.003	0.001	0.002
20 Year	-0.029***	-0.034***	-0.006*	-0.011***	-0.003***	-0.006**
	0.007	*0.006*	*0.003*	0.003	0.001	0.002
Note: *p<0.1** p<0.05***p<0.01						