HUGGETT JR., ROBERT JAMES. Fire in the Wildland-Urban Interface: An Examination of the Effects of Wildfire on Residential Property Markets. (Under the direction of Dr. Raymond B. Palmquist.)

ABSTRACT

Housing markets near forests and wildland should capitalize into prices the value of forest amenities such as recreational opportunities, attractive scenery, and clean air. The expanding wildland-urban interface has made wildfire a frequently discussed and contentious public policy issue over the past decade. As residential communities expand into natural areas, more lives and property are placed at risk of death and destruction from wildfire. Housing markets are impacted by both the mere presence of fire risk as well as the damage to forest amenities and property that accompanies a wildfire. The purpose of this research is to empirically identify these responses. A data set comprised of residential housing sales from 1992-1996 in Chelan County, Washington was used to determine how the market responded to the 1994 fires in the Wenatchee National Forest that burned over 180,000 acres. The results indicate a decrease in the willingness to pay to live near the burned area for a six-month period in early 1995. There is no change in the willingness to pay to live near areas of relatively higher fire risk defined by higher fuel levels, which can be interpreted as a lack of support for collective protective measures that would reduce fuels. Additionally, the hedonic price for a fire-resistant roof increases gradually for 18 months before dropping to pre-fire levels in the second half of 1996. This result indicates that the subjective or perceived risk of property damage from wildfire behaved in a similar fashion and suggests either a risk threshold below which the household disregards the risk of fire or a general lack of awareness of risk.

Fire in the Wildland-Urban Interface: An Examination of the Effects of Wildfire on Residential Property Markets

by

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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

ECONOMICS

Raleigh

2003

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DEDICATION

My dissertation is dedicated to my wonderful wife, Cindy. Her hard work, patience, and encouragement made this possible. When I thought that I could not or did not want to go on, her smiling face made me believe that I could finish. I could not have made it through the last five years without her. Thank you, buddy. We did it together.

BIOGRAPHY

Robert was born in Williamsburg, Virginia in 1969. He graduated from James Madison University in Harrisonburg, Virginia in 1991. Even though he has lived in North Carolina the past nine years, he remains a fiercely loyal Virginian. He enjoys listening to music, playing guitar, and exercising. Robert and his wife Cindy reside in Raleigh.

ACKNOWLEDGEMENTS

Like most things in life, I have not done this alone. I again acknowledge my wife's love and support through this ordeal. My parents provided the background and foundation for path I have chosen. I guess you can run, but you cannot hide. I would like to thank the graduate economics program at NCSU for providing me with this opportunity. The United States Department of Agriculture and the Forest Service deserve special recognition for the funding opportunities that I have received throughout my graduate school experience. Forest Service Research Work Unit SRS-4851 in Research Triangle Park has been a source of support and inspiration for almost three years. Thanks to Karen Abt and Jeff Prestemon for working with me to make this association with the work unit possible. Karen's advice and counsel not only provided the idea for this work, but have also shaped it considerably. Dave Butry has been an invaluable source of information on Arcview and GIS. Tom Holmes, Evan Mercer, and John Pye have availed themselves as sounding boards for numerous ideas. The Chelan County Assessor's Office provided me with the housing transaction data used in the empirical application. The assistance of Paula Cox, Hiro Harui, Jean Postlethwaite, and Sue Pullman is gratefully acknowledged. Their patience in the face of my constant pestering has been extraordinary. I am fortunate to have such a supportive committee. Ray Palmquist's patience and assistance has brought me from a rough idea and a messy data set to a completed dissertation in one year's time. Russell Lamb, Subhrendu Pattanayak, and Dan Phaneuf have given their time and energy to bettering this project- thank you all. Of course, despite the help of all of these, any mistakes remain my own.

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LIST OF SYMBOLS

Symbol	Definition
α^S	The subjective or perceived risk of property damage from wildfire
α^C	The subjective or perceived risk of neighborhood fire risk
α^O	The objective or true risk of property damage from wildfire
A	Private self-protection or averting behavior
G	Collective protection or averting behavior
I	The level of information
P_H	The hedonic price function
Q	Forest condition or quality in the unburned state
Q^F	Forest condition or quality in the burned state
v	Utility in the no-wildfire state
v^C	Utility in the wildfire state where no property is damaged
v^S	Utility in the wildfire state where property is damaged
$\mathbf{W}$	A vector of other variables that influence collective risk
X	A numeraire good
Y	Income in the no-wildfire state
Y^C	Income in the wildfire state where no property is damaged
Y^S	Income in the wildfire state where property is damaged
$\mathbf{Z}$	A vector of housing characteristics; Z_j is the jth characteristic

I. INTRODUCTION

OVERVIEW

Wildfire is one of the most frequently encountered natural hazards in the American west. From 1990 to 2000, roughly 91 percent of large fires (fires over 1,000 acres in size) and 96 percent of acres burned by large fires have occurred in the interior west of the United States (GAO, 1999). Frequent, low-intensity fires that cleared brush and small-diameter fuels have historically characterized the fire regime in the interior west. This historic regime has, in general, changed to one dominated by less-frequent, high-intensity wildfires. This shift has occurred for several reasons. More than half a century of suppressing almost all fires has resulted in a buildup of brush and small-diameter fuels that carry fire to the crowns of larger trees. Additionally, the share of forest vegetation in less-wildfire tolerant species has increased as a result of grazing practices, timber harvesting that removed the more fire-tolerant trees, clear-cutting that promoted the growth of less fire-tolerant types of trees and vegetation, and the introduction of nonnative species (GAO, 1998). These more intense fires are in large part a result of denser stands filled with both fuel that has accumulated in the absence of the less intense fires as well as less fire-adapted species. In combination with extreme weather events such as the *El Nino/La Nina* cycle and the risk to human lives and property associated with an ever-expanding wildland urban interface, the change in fire regime has led to a significant allocation of resources to both reduce the risk of fires and suppress them once they start. According to *Managing the Impact of Wildfires on Communities and the Environment: A Report to the President In Response to the Wildfires of*

2000, suppression resources during the 2000 fire season included 29,000 people, 1,200 fire engines, 240 helicopters, and 50 airtankers.

Risk reduction and suppression are not the only economically relevant costs of wildfire. Timber market dislocations, lost tourism and recreation, and increased health-related expenditures all result from large fire events. Wildfire can have a devastating effect on communities and surrounding environmental amenities. Wildfires that destroy large tracts of forest result in a loss of scenic beauty and recreation opportunities. Additional issues facing communities are the loss of wildlife habitat, decreased water quality, the increased threat of floods and erosion, and the questions concerning the salvage of any remaining timber. The fires in northeastern Florida in 1998, concentrated in the St. John's Water Management District, destroyed 500,000 acres. The result was $620 million in economic losses, including $100 million in federal suppression expenditures, $138 million in lost tourism, $354 million in timber losses and market distortions, and $10 million in insured property (Mercer et al. 2000).

Wildfire and Property Markets

Damage and destruction to property is the primary impact of wildfires on property values. However, wildfire need not damage or destroy a house to have its effects felt in property markets. The presence of wildfire risk alone (without the realization of fire) should be capitalized in the price of a residence. Because wildfire risk varies spatially and households have preferences for varying levels of risk, a lower value should be assigned to a house with higher fire risk than a house with a lower level of fire risk.

A wildfire event that damages a forest resource near a property can also have an impact on that property's price. The price of the house should capture the household's willingness to pay to live near woodland because forests provide benefits to the household. A wildfire can impact these benefits in two ways. The first is a pure amenity aspect. Housing markets located near forested land provide residents with visual and aesthetic amenities that may be damaged during a fire. The loss of standing timber and a blackened, denuded landscape can deduct from a forest's aesthetic value.

The second way fire impacts property values through damage to the forest resource is reduced access to recreational opportunities. Decreased water quality, impaired wildlife habitat, and damaged trails and roads can reduce the demand for forest recreation. Englin et al. (1996) observed losses of $15.46 per canoe trip in 1993 from the 1983 Long Lake fire in Nopiming Park, Manitoba. Loomis et al. (2001) find that the number of years since a crown fire had a positive effect on the demand for mountain biking trips and value per trip. However hiking trips and value per trip decreased in the years following a crown fire. Note that the pure amenity and recreation qualities of woodland are not necessarily independent. The desirability of forests for recreation purposes often depends on the scenic amenities the forest provides.

From the assumptions made above, changes in the risk of wildfire and changes in the level of amenity provided by the forest resource will likely be accompanied by changes in property values. However it can be difficult to separate out the effects of fire risk and the levels of forest amenity. This is because significant correlation may exist between fire risk and amenity level. It is not hard to imagine that areas with high scenic beauty might also be those most at risk to a catastrophic fire event. To assist in this discussion, consider a simple amenity/risk matrix that divides amenity and risk into two categories, high and low, for a representative household.

	Risk Level	
Amenity Level	Low	High
Low	Low, Low	Low, High
High	High, Low	High, High

Figure 1: Risk level vs. amenity level

For example, a house located near a forest that provides a high level of recreational opportunities may also be exposed to a high risk for wildfire, corresponding to (high, high) in terms of Figure 1. In contrast, a community may implement a plan to reduce the risk of fire in its immediate surrounds without reducing the level of forest resources available for recreation. This would correspond to (high, low) in Figure 1. Given an amenity level (low or high), comparing housing prices between communities with different levels of risk (across a row in terms of Figure 1) can provide insight into how households value risk. Similarly, given a level of wildfire risk (low or high), examining the difference in housing prices across the two amenity levels (down a column in terms of Figure 1) can allow me to place a value on the forest resource.

RESEARCH OBJECTIVES

The risk of catastrophic wildfire is an increasing concern to multiple stakeholders as the boundary between residential communities and wilderness areas, the wildland-urban interface, expands. The economic effects of large wildfires extend beyond burned forest and destroyed structures. As the focus of fire suppression has shifted from fighting all fires to protecting neighborhoods, homes, and property along with the forest amenities near human development, the examination of how wildfire impacts property markets has become crucial.

Only one study has analyzed the behavior of housing prices in response to a wildfire event. In early 2001, PricewaterhouseCoopers performed an analysis of how the Los Alamos, New Mexico real estate market responded to the Cerro Grande fire that occurred the previous summer. The fire resulted in 48,000 burned acres, 300 damaged or destroyed residential structures, and 18,000 residents evacuated (*Report to the President*, 2000). Examining prices before and after the fire, the results indicated that housing prices did drop temporarily in the fire's aftermath. Although the PricewaterhouseCoopers study breaks ground by being the first to look at how a residential property market responds to a fire event, it is not without shortcomings. Most significantly the methodology employed to estimate the impact of the fire on the price of a house was a simple dummy variable, before fire versus after fire. Further, the report did not attempt to uncover the mechanism that brought about the decline. As discussed above, wildfires can affect property markets through the diminution of the forest resource and the risk of fire itself. Finally, the post-fire time series examined in the PricewaterhouseCoopers report was very short compared to the pre-fire time series. With several years of pre-fire data and only a little over one-half year of post-fire data, the results obtained may not be an accurate reflection of what transpired in the Los Alamos market.

Over 180,000 acres burned in the Wenatchee National Forest in central Washington in the summer of 1994, destroying 37 homes and 76 outbuildings (Carroll et al. 2000). Using housing data from Chelan County, my research quantifies the effect of wildfire on residential property markets. This will be done two ways. The first is through the pure risk component of fire. Wildfire risk varies spatially, so knowledge of property locations and the level of wildfire risk surrounding them will allow me to estimate the impact of differential risk of wildfire on housing prices. Via a Geographic Information System (GIS), property locations can be assigned a level of wildfire risk based on several proxies for risk.

The second effect of the 1994 fires is the impact on the surrounding forest resource. The occurrence of wildfire in an area near a residential property market provides an opportunity to study the response of housing prices to a decline in resource amenity. In this sense analyzing property markets in the presence of a wildfire event is a natural experiment: the wildfire destroys a pre-existing resource allowing the researcher to examine housing prices under two discrete levels of amenity. Looking at a location that experiences a catastrophic wildfire event in comparison to another location with an undamaged forest while controlling for differential wildfire risk will provide a means of measuring the impact on housing prices of reduced forest amenity due to wildfire. My results show a positive willingness to pay to live near the national forest that does not change over the sample time frame. Prior to the fires, households exhibit a positive willingness to pay to live near the area that would eventually burn. However, the coefficient for distance to the burned area turns positive for a six-month period following the fires when considering a half-kilometer neighborhood of vegetative risk around the house.

CONTRIBUTIONS

This research makes several contributions. First, it fills in a gap in the literature by attempting to empirically measure the relationship between wildfire and property markets by accounting for spatial variability in fire risk and the change in amenity level brought about by a fire event. Further, my results indicate how wildfires affect the valuation of private and public risk reduction. Individuals and households can privately take action in response to wildfire risk. Incorporating fire-resistant roofing and siding material, installing double pane windows, and clearing combustible brush and debris to create a perimeter of defensible space around a structure are examples of private actions. My results show an increasing willingness to pay for a Class A fire resistant roof for two years following the fires.

Collective or publicly funded responses typically involve vegetation management strategies on public lands. Activities such as prescribed burning and prescribed wildfire, mechanical thinning, and the creation of firebreaks fall into this category. From 1994 to 2000, the Forest Service and Bureau of Land Management increased the number of acres managed to reduce fire from 500,000 to almost 2.4 million (*Report to the President*, 2000). The debate over collective risk reduction strategies can become heated and contentious due to the conflicting views of forest and wildland stakeholders. The support for or opposition to vegetation management is hardly black and white, but some generalizations can be made. On one hand, recreational groups involved in backpacking, hunting, or fishing may view vegetation management strategies with suspicion if they feel there is a chance these activities will result in decreased forest quality. Likewise, other conservation or environmental groups may be opposed to such measures if there is the perception they take advantage of fire risk to promote logging in areas currently off-limits to harvest. Still others feel that the only way to return the forests to their historical, lower risk levels is to just let them burn. Finally, some property owners may be opposed to prescribed burning because of the chance of escape. The

47,000-acre Cerro Grande fire began as a prescribed burn by the National Park Service. Support for vegetation management strategies comes from those that view such activities as effective in reducing fire risk as well as from industries that stand to gain from increased resource extraction as a result of the opening of areas on public lands previously closed to logging. The coefficient estimates of the risk proxies in my estimations do not provide any insight into the willingness to pay for collective risk reduction.

As the awareness of wildfire risk and the damage created by catastrophic wildfire events increases, the public policy debate on the proper course of action to mitigate risk and losses gains in importance and visibility. Several issues are crucial to this discussion, with the common thread being the role of public and private responses. The market for wildfire risk reduction is comprised of the private and collective averting behaviors described above. Where markets are not well defined or participation is limited, alternative strategies exist to mitigate risk. These include restrictions on development in high-risk areas and ordinances on materials used in housing construction (roofing, siding, windows). However, these may not be well-accepted solutions if homeowners and residents view government mandates as intrusive and overbearing. How households value public and private strategies and how these valuations respond to a wildfire event is an important policy question. Should government institutions allocate funds to collectively reduce risk, or should households be left to their own devices to mitigate risk on their own individual properties? By examining the behavior of the value that households place on private and public risk reduction over time, I can determine how a wildfire event changes preferences for these strategies.

A final contribution of this research is an analysis of the behavior of household risk perceptions in response to the information communicated by a fire event. The role of information in individual assessments of wildfire risk cannot be overstated. Public information campaigns, the news media, and extreme events themselves all convey information that helps form risk perceptions. In the United States, FIREWISE seeks to provide information on wildfire risks and actions that can be taken to mitigate risk to households in the wildland-urban interface. The news media plays a powerful role in the public's perceptions of risk. The wildfire season in the western United States is typically the summer, when news may be otherwise thin. Scenes of towering flames and burning houses accompanied by emotionally distraught residents are commonplace on national evening news programs from June through August. Finally, residing near a wildfire event, independent of sensational news coverage, can have a profound effect on risk perceptions. Based on the coefficient estimates of the fire-resistant roof, I will show that the perceived risk of property damage increased following the fires. I argue that this is a result of the increased level of information regarding property risk. After some point this risk declined. It is unclear whether decrease was due to a decrease in the information level, or a risk threshold. However the distinction is important because the effectiveness of policy formulations regarding risk education programs will be different under the two scenarios.

The paper will begin with a literature review. The first section will focus on previous studies that have looked at the impact of forested woodland and open space on property markets. The second section deals with the risk aspect and reviews work on incorporating risk in property value models. There are no existing studies that explicitly examine wildfire risk, but the models and methods used in the analysis of risk from other natural disasters (earthquakes) and environmental hazards are useful in considering how to incorporate risk in both a theoretical and empirical context. This is followed by the development of a theoretical model of subjective risk and household utility maximization. A discussion of the study area, the data, and the details of the estimating equation are presented next. Estimation results are presented and analyzed. The initial estimation suggests that the 1994 Chelan fires had significant, but transient effects on the hedonic prices of amenity and risk proxies. The theoretical model is extended and further developed in the policy section to infer the willingness to pay for private and collective averting activities and to determine how subjective risk assessments changed in response to the fire. Interpretations of the results, the implications for policy, and extensions are considered last.

II. LITERATURE REVIEW

THE FOREST AS AN AMENITY

The use of hedonic models is a popular method to explain the effect of forests and woodland on residential property markets. The value of trees on a residential parcel (on-parcel trees) is the first area of interest, primarily the purview of real estate appraisal and arboricultural literature. Another category of literature focuses on forests and open space surrounding a parcel. These studies use two main methods to describe woodland's influence on a property's price: distance to a forest amenity and some measure of forest cover or open space around a property. An increase in distance to a forest amenity is expected to have a negative impact on property values. Measures of forest cover or open space can have conflicting impacts, depending on how the variable is measured and other variables that describe the surrounding environment.

All of the studies examined use a variety of structural, neighborhood, and environmental variables to control for observed heterogeneity within a sample. Structural variables include information on a house and the land it occupies, such as square feet, age, acres, etc. Neighborhood variables describe the immediate environment surrounding a parcel. They can be socio-economic (average income, education) or physical (distance to urban center, access to highways). Environmental variables incorporate broader and more far reaching characteristics of a parcel's surroundings. Distance to a forest, lake, or river and measures of landscape diversity and fragmentation are examples.

This literature review will contribute to my work in several ways. First, it will reveal the various methods that have been used to measure the value of the forest amenity to a household. Distance measures are the most common, but recent works have also used neighborhood variables such as the percentage of the area surrounding a property that is in forest cover or open space. Comparing the estimation results in these studies to my own will enable me to determine if my results are reasonable. A common theme that emerges from the previous work is that the forest is rarely viewed as anything other than an amenity. The risk of wildfire that is associated with either living near a forest or having a neighborhood that is characterized by a high level of fuels is considered in only one study. Several other studies found negative relationships between forest variables and housing prices but do not introduce fire risk as an explanation. This indicates that there is sufficient "daylight" in the literature on woodland and housing prices to warrant this investigation, and for it to make a contribution in the understanding of how households value forests. The review will begin with a summary of three on-parcel studies followed by works concerning surrounding forest and open-space amenities.

Tree Cover on Residential Property

While the proposed work focuses on the value of off-parcel trees and woodland, looking at previous studies on the value of on-parcel tree cover is useful. At the very least, the marginal price for trees located on residential property represent (in part) the amenity value of having tree cover at a zero distance from the property. Dombrow, Rodriguez, and Sirmans (2000) find that the presence of mature trees (any tree greater than nine inches in diameter) on a sample of residential sites in Baton Rouge, Louisiana added 1.86% to the price of a house. In a study of sixty Manchester, Connecticut residential properties, Morales (1980) reports that 6% to 9% of the sales price of houses with "good tree cover" (fifty to sixty percent of the lot in mature tree cover) can be attributed to the tree cover. In a study of residential properties in Athens, Georgia Anderson and Cordell (1985) report that trees in the front yard contribute 3% to 5% to the sales price at the mean.

Table 1. On-parcel tree studies

Author	Location	Variable	Result
Dombrow et al. (2000)	Baton Rouge, LA	Mature Tree Cover =1, 0 Otherwise	The presence of mature trees increases price by 1.86%***
Morales (1980)	Manchester, CT	Mature Tree Cover =1, 0 Otherwise	Mature tree cover increases price by 6%-9%$^{+}$
Anderson & Cordell (1985)	Athens, GA	Number of Trees in Front Yard	Trees increase price by 3%-5% **

*** significant at 1%
** significant at 5%
$^{+}$ significance not reported

Forests and Open-Space as an Off-Parcel Amenity

The evaluation of the value of off-parcel tree cover and woodland to residential property seems to fall into two general categories. The first is in the context of urban forest amenities. These usually refer to “greenbelts”, areas of open space within or around a broader urban area, or other urban forests or wooded recreation areas. Forests and woodland are the second category.

Greenbelts and Urban Tree Cover

Lee and Linneman (1998) examine the impact of Seoul’s greenbelt on land markets. They create a structural model where the level of greenbelt consumed is a function of the number of users and accessibility to the greenbelt. From this model, they expect land values to decrease with an increase in distance to the greenbelt. Lower travel costs for a recreational trip to the greenbelt, scenic amenities, and clean air amenities are responsible for this distance gradient. Increased congestion may also cause changes in the distance gradient over time. Their empirical results find that land values fall by 4% for each one-kilometer increase in distance from the greenbelt. The authors suggest that this is a relatively large estimate.

Correll, Lillydahl, and Singell (1978) evaluate the effect of distance to greenbelts on residential property markets in Boulder, Colorado. The authors explain that differences in prices that can be attributed to the amenity are equal to the discounted value of the stream of amenity benefits from the greenbelt, which conveys two public good aspects. The first is a pure public good that all the residents of Boulder can consume such as scenic backdrop and option value (residents may pay to preserve greenbelt open space even though they have no plans to use it at present). The second is a quasi-public good aspect that benefits those who live nearest to the greenbelt. Thus distance creates an exclusion effect. Because consumption is therefore rival, property values should include a rent for greenbelt amenity that should decline with distance to the greenbelt. This is the general theoretical foundation for the value of proximity to a forest resource. The empirical model, which regresses price on distance to the nearest greenbelt estimates that there is a $13.78 drop in price for a one-meter increase in distance to a greenbelt (for their aggregate sample). An elevation variable to examine the value of view was included in one specification but was found to have an insignificant coefficient. The authors indicate that lower elevation may not necessarily mean a worse view.

Tryväinen and Miettinen (2000) look at the value of urban forests based on a study of the sales of terrace residences in the district of Salo, Finland. The authors believe that recreation and scenic amenities are the largest benefit sources of urban forests, with clean air and quiet from urban congestion secondary benefits. Four variables are used to capture the amenities that urban forests provide: distance to the nearest wooded recreation area, distance to the nearest forested area (or forest park), view of a forest (1 = yes, 0 = no), and view of a park (1 = yes, 0 = no). In the first empirical specification, an increase of one kilometer to a forested park decreases the selling price for a terrace house by 5.7% while a forest view increases the same price by 4.9%. A second specification broke down the distance to the nearest forest park into five categories (adding four dummy variables to the model). The percentage increase in selling price was highest for properties closest to the forest park (.005 - .999 km) and declined as distance increased. A forest view in this specification added 4.2% to the price of a house.

In a closely related study, Tryväinen (1997) studies how urban forests affect apartment sales prices in North Carelia, Finland. From the empirical results, an additional 100 meters to a recreation area decreases the price per square meter by 1.6 % while an additional 100 meters to a forest park *increases* the price per square meter by 14.6%. The author gives several possible explanations for this result, but fire risk is not one of them. A one percent increase in green space in an apartment's housing district increased the price per square meter by .3%.

Forests and Woodland

The studies in this category rely primarily on measures of forest cover (as opposed to distance to a forest) to describe the amenity. Geoghegan, Wainger, and Bockstael (1997) assert that residential property values are affected by the pattern of land uses around a given area. In one specification, open space is measured at .1 km and 1 km buffers around each property. A 1% increase in open space within a .1 km buffer increases a property's price by

1.89%, while a property's price decreases 3.4% with a 1% increase in open space within a 1 km buffer. These results indicate that only open space in the household's immediate neighborhood is valued.

Geoghegan (2002) examines how the percentage of land open-space within a 1.6 km buffer (one mile or a 20-minute walk) of a property affects property values in Howard County, Maryland. Two types of open-space are incorporated: permanent, such as parks and other areas with conservation easements that cannot be developed, and developable (private forested and agricultural land). A 1% increase in permanent and developable open-space increases price by 25.7% and 7.4% respectively. The author explains that this suggests that households place more value on open space that is not subject to future development. In a study of an urban watershed in New Haven, Connecticut, Acharya and Bennett (2001) find that a 1% increase in open-space within a 1.6 km radius increases selling price by .06%. This is sharply lower than Geoghegan's result.

Schultz and King (2001) look at the sensitivity of hedonic results to varying levels of land use aggregation in the area of Tucson, Arizona. Their results indicate that aggregating at differing spatial scales (census block, block group, or tract) does not affect the estimated coefficients jointly. However, the authors report some complex relationships between housing prices and differing types of open space. At the census block level, being a tenth of a mile closer to large natural resource areas increases a house's price by $59. Being a tenth of mile closer to a neighborhood park decreases price by $469. Additional proximity to Class I wildlife habitat decreases price by $108 while price increases $349 for additional proximity to Class II wildlife habitat. The authors assert that Class I is more ecologically critical and pristine than Class II and that the negative value associated with Class I may be due to the risk of flooding associated with these areas. This type of analysis is interesting because it uses various measures of open space amenities and at least implicitly takes into account the risk associated with natural resource spillovers

Powe, Garrod, Brunsdson, and Willis (1997) use GIS to estimate the value of woodland in Southampton and New Forest, Great Britain. A forest access index is developed and calculated for each house that incorporates both the area and proximity of forested land.

$$\text{Forest access index} = \sum_i (\text{area}_i/\text{distance}_i^{\,2})$$

A 1% increase in the index results in a .046% increase in price.

Garrod and Willis (1992b) and Garrod (1994) maintain that the willingness to pay for a residential property depends (among other things) on neighborhood and environmental characteristics. In a study that includes almost 5,000 km^2 of central England and 2,000 observations, they estimate how the approximate cover by forests, water, and parkland ("countryside characteristics") influences housing prices. The empirical results indicated that the continuous measure of forest cover was not significant. However a dichotomous variable indicating whether there was at least 20% woodland cover in the 1 km square that a property was located was significant. The proximity of at least 20% woodland cover raised a houses price by 7.1%.

In a separate study, Garrod and Willis (1992a, 1992c) and Willis and Garrod (1992) examine how different forest types influence property values. The authors sought to model both the willingness to pay to be proximal to a forest amenity and the willingness to pay for the pure amenity value of forests. This study utilized a sample of over 1,000 properties located within a 1 km square of Forestry Commission land in Great Britain. The variable of interest is the percentage of forested area covered by six age groups in three categories of trees (broadleaf, larch & pine, and other conifers) in each 1 km square. The percentage of forested area in broadleaf increased price by 42.81 pounds, while the percentage of forest in conifers decreased price by 141 pounds. The larch and pine variable was not significant (and therefore not reported).

Reporting findings similar to that of Geoghegan et al. (1997), Wells (2001) develops measures of the level of forest canopy at 100- and 500-meter buffers from residential properties in Flagstaff, Arizona. Canopy closure, the percentage of stand area that occupied by tree crowns, is a proxy for stand density. His results indicate a .028% increase in price for each additional square meter of medium canopy cover within a 100-meter buffer. With a 500-meter buffer, price increased .056% for a 1% increase in the average level of medium canopy cover but decreased .17% for a similar increase in the average level of high canopy cover. The paper suggests that the decrease due to high canopy cover at the 500-meter buffer may reflect households' preferences for woodland with lower fuel loads. This is the only study to mention wildfire risk as an explanation for forest variables that decrease the price of a house. Mansfield et al. (2002) use a variety of variables to account for the effect of urban forests on the price of residential parcels in the Research Triangle area of North Carolina. In a model including mean "greenness" price drops .043% for every additional ten meters from an institutional forest and .014% for every additional ten meters from a private forest block of forty acres or more. Table 2 summarizes the results of the studies looking at housing prices and forests and open-space.

Table 2: Summary of studies focusing on forests and open-space surrounding a parcel

Author	Location	Variable	Result
Lee & Linneman (1998)	Seoul, Korea	Dist. to Greenbelt (km)	4% dec. *** in price with a 1 km inc.
Correll et al. (1978)	Boulder, CO	Dist. to Greenbelt (m)	$13.78 dec.** in price with a 1 m inc.
Tryväinen & Miettinen (2000)	Salo, Finland	Dist. to Forested Park (km), Forest View = 1, 0 otherwise	5.7% dec.*** in price with a 1 km inc., 4.9% inc.*** with forested view
Tryväinen (1997)	North Carelia, Finland	Dist. to Wooded Rec. Area, Dist. to Forested Park, Relative Amount of Forested Area	1.6% dec. ** & 14.6% inc. *** in price/m^2 w/ addt'l 100 meters to a rec. area & forest park respectively; .3% inc. *** in price/m^2 with a 1% inc. in green space
Geoghegan et al. (1997)	Patuxent Watershed, MD	Percentage of open space at .1 & 1 km buffers	Price inc. of 1.89%***, & dec. of 3.4%*** with a 1% inc. in open space given .1 & 1 km buffers respectively
Geoghegan (2002)	Howard County, MD	Proportion of 1.6 km radius in permanent and developable open-space	Inc. in price of 7.4%**and 25.7%*** with 1% inc. in permanent and developable open-space respectively
Acharya & Bennett (2001)	New Haven County, CT	Open space w/in a 1.6 km radius	1% inc. in open-space w/in a 1 mile radius inc. price by .06%***.
Schultz & King (2001)	Tucson, AZ	Proximity to large nat. res. areas, neighborhood parks, and wildlife areas	Add'l proximity inc. price by $59** for large nat. res. areas, dec. price by $469*** for parks, dec. price by $108*** for Class I habitat, and inc. price by $349*** for Class II habitat.
Powe et al. (1997)	Great Britain	Forest Access Index (see text)	.046% inc.*** in price with a 1% inc. in the index
Garrod & Willis (1992b)	Central England	20% forest cover = 1, 0 otherwise	7.1 % inc.*** in price w/ proximity to 20% woodland
Garrod & Willis (1992a)	Great Britain	Proportion of area in three tree types	42.81 pound inc.*** & 141 pound dec.*** in price with a 1% inc. in broadleaf area and conifer area respectively
Wells (2001)	Flagstaff, AZ	m^2 of med. and high canopy cover w/in 100 m and 500 m buffers	.028% inc.** in price w/ 1% inc. in med. canopy w/in 100 m buffer; .056% inc.*** and .17% dec.*** in price w/ 1% inc. in med. & high canopy w/in 500 m buffer respectively
Mansfield, et al. (2002)	Research Triangle, NC	Distance to institutional and private forest block boundaries (m)	.043% dec. *** and .014% dec.** in price for a 10 m inc. to an institutional and private forest block respectively

*** significant at 1%
** significant at 5%
* significant at 10%

A variety of variables, serving as forest and amenity proxies, are used in these works. Distance, which embodies qualities such as viewshed, recreation access, and air quality, is the most popular. More complex spatial variables such as those used by Geoghegan et al. (1997) and Wells (2002) connote different values. Density measures represent the level of forest fragmentation and fuel loading. Only two of the above papers make any connection between natural resources and risk. Wells (2002) suggests that his results imply a willingness to pay to reduce the fuel levels associated with high canopy. Schulz and King (2001) note that the prospect of flooding in more pristine areas may explain their results.

There is an explanation for this lack of conjecture on the role that natural resource risk plays in determining housing prices. It is difficult to separate out the amenity and risk qualities embodied in a forest resource. Many natural resources present the risk of disamenities in addition to the amenities they provide. Rivers may flood. Coastal areas are at risk of violent storms, hurricanes, and tidal forces. Wildfire threatens forests and woodland. The same measures that seek to capture the positive spillovers from a resource may also represent some measure of risk to the household from that resource. For example, decreasing the distance to the forest boundary increases viewshed and recreation opportunities but also increases the risk of property damage due to a fire. In the empirical application to my work, I will use distance to the forest to proxy for the forest amenity and neighborhood vegetation density to proxy for the risk component. A short examination of previous hedonic work on risk will assist in formulating the theoretical model and developing the estimation strategy.

RISK

Even though there are no empirical studies of the effect of wildfire risk on housing prices, the literature on the economic aspects of risk is massive. Several previous works on the effects of risk on residential property markets can provide context from both theoretical and empirical perspectives. The literature dealing with other natural disasters such as earthquakes and volcanoes is especially applicable in thinking about wildfire risk, but valuable insight can be obtained from the work on risk from environmental hazards.

Bernknopf et al. (1990) consider how volcano and earthquake hazard notices issued for Mammoth Lakes, California in the early 1980s affected property values. Their study relied on a survey instrument that indicated if the household was aware of the hazards at the time the house was purchased. A second measure of risk was the date of purchase- before or after the issuance of risk notices. They find losses of 8.2% for hazard knowledge and 11.4% from the risk notices. McClelland et al. (1990) also use a survey instrument to measure the subjective assessment of risk from a landfill in Los Angeles, CA. Survey respondents and housing sales were matched to geographic areas. The risk proxy is the proportion of respondents in an area that believed they were in the high-risk group. An increase of 10% in the proportion of respondents in a given neighborhood that are in the high risk category decreased a house's price by 1.5% prior to the closing of the landfill. After the landfill closed, the proportion of respondents in the high-risk group fell by 24%. This corresponded to a 3.7% increase in price.

Beron et al. (1997) look at the response of property markets in the San Francisco Bay area to the Loma Prieta earthquake of 1989. Their theoretical model is based on the relationship between perceived or subjective risk and the true or objective risk level. Their first measure of subjective risk is the expected lifetime potential damage (as a percentage of a property's value) due to an earthquake. This measure is instrumented in a first-stage estimation and the estimated value is used in the second-stage hedonic equation. A second risk proxy is a dichotomous variable indicating if a property is located in an area with susceptibility to earthquakes (this is included in both the first- and second-stage equations). This captures the "institutional effect" of risk perceptions. The authors state that their findings indicate that perceptions of risk change with the occurrence of an event. In this case, they claim that the consumers overestimated earthquake risk prior to the event and adjusted their risk perceptions downward afterward. A marginal change in potential damage was responsible for a 6.5% ($20,000) decline in a house's value prior to the earthquake and a 4.2% ($13,000) decline afterward. Being located in a fault zone decreased a house's price by 3.8% ($11,800) prior and 2.8% ($8,800) afterward.

Kask and Maani (1992) derive a model of risk perceptions and explicitly show how information changes subjective risk assessments. Information can increase or decrease the subjective risk level, depending on whether the subjective level is initially below or above the endowed, or true risk level. Although the subjective risk level is unobserved, the change in the hedonic price of self-protection allows them to determine if perceived risk is increasing or decreasing.

Gayer et al. (2000) examine cancer risk from Superfund sites in Grand Rapids, Michigan and housing price responses. Their theoretical model incorporates risk in an expected utility framework. Risk is a variable of the hedonic function but does not enter the utility function directly. This theoretical specification is consistent with Freeman, Gayer (2000), and McConnell (1993). The marginal price for risk reduction is the difference in utility in the two uncertain states divided by the expected marginal utility of income. As in Beron et al. (1997) the risk measure, the lifetime excess cancer risk from Superfund sites, is instrumented on a variety of variables in a first-stage estimation and estimated values are used in the second-stage hedonic equation. Gayer (2000) also uses a two-stage estimation to control for possible endogeneity of risk.

These studies provide a foundation for constructing my theoretical model and estimation procedure. The role of subjective risk should be explicitly defined. The work of Beron et al. (1997) and Kask and Maani (1992) will be very important in developing the theoretical model in the next section, as well as in uncovering the behavior of subjective risk in response to a catastrophic wildfire event in the policy chapter. McConnell's (1993) model that incorporates resource proxies (such as distance) as both elements of risk and sources of utility reveals the difficulty in separating out the impacts of positive and negative amenities. I hope to untangle these confounding effects by including measures of forests that embody the risk component of forestland, allowing the distance variables to represent only the amenity attributes and other measures of surrounding vegetation to proxy for the level of neighborhood fire risk.

III. THE MODEL

As discussed in the literature review, Rosen's (1974) hedonic model provides a framework to examine how forest amenities contribute to residential property values. The theory underlying the hedonic model states that consumer preferences for the structural, neighborhood, and environmental qualities of a house determine its price (Palmquist). The price of a house (P_H) is the sum of its discounted future rents or benefits (B)

$$(1) \qquad P_H = \sum_{t=1}^{T} \frac{B_t}{(1+r)^t}$$

where r is the rate of discount and the expected life of the house is T. A property's price embodies the expected changes in forest condition in its neighborhood and risk to the property due to wildfire.

The hedonic model considered here will account for the effects of wildfire on property markets in two ways- the change in forest amenity due to a wildfire and the presence of wildfire risk alone. Consider first the change in forest quality. Suppose that households enjoy forests for both pure amenity (scenic beauty) and recreation uses. A property's price should therefore be dependent on forest quality through its viewshed and opportunities for forest recreation. A wildfire event that impairs the forest's pure amenity and recreation properties would have an impact on the property's value. The household must consider this risk and the associated change in forest amenity when it determines future benefits. Freeman formulates a hedonic model in the context of uncertainty where a house's price is dependent on the level of damage to the resource in the risky state. In this model the price (P_H) will be a function of a baseline level of forest quality where the probabilities of the different states of the world determine the level of future quality.

The second aspect of wildfire to be included in the hedonic model is risk of damage to the house. Hedonic models that do not include both a measure of the resource and the risk of damage if both vary independently across space will be misspecified (Freeman 1993). Wildfire is not a deterministic process, but instead is characterized by a probability distribution. Households have preferences for risk. Since wildfire risk varies spatially (as well as temporally) and therefore residential communities will experience different levels of risk, the price of a house should reflect the assessment of prevailing wildfire risk. However, as previously explained the subjective assessment of risk may differ from the true or objective risk level. To consider this possibility, I will develop a model of subjective risk based on the work of Beron et al. (1997) and Kask and Maani (1992). The usefulness of this model will become clear when the role of information and the behavior of the hedonic prices from the estimation results are used to explain the evolution of perceived risk in the study area.

A MODEL OF SUBJECTIVE RISK

In modeling household behavior in the presence of wildfire risk, two types of risk must be considered. The first is the perceived or subjective risk to the household's neighborhood or surrounding community. This risk implies the probability of damage to the surrounding area due to a wildfire event. It should be dependent on the condition of the forest, the level of collective or publicly funded averting behavior, the level of information about risk available to the household, and other variables. Collective or public averting activities, G, are those that are undertaken by public agencies. Prescribed burning and thinning small diameter fuels and brush from public lands (state and national forests, state and national parks) are examples. It is unlikely that the household can perfectly identify the true, or objective, community risk level. Therefore the perceived level of community risk is likely to differ from the true level. Smith (1996) explains that an individual's hazard perception is shaped by previous experience with the hazard, current attitudes, expectations of the future, and personality and values. Community risk is defined as

(2) $\alpha^{C} = \alpha^{C}(G, Q, \overline{\mathbf{W}}, \bar{I})$ where

G is the level of collective or publicly funded averting behavior

Q is a state variable describing the condition of the forest resource

$\overline{\mathbf{W}}$ is a vector of other variables, which influence the level of collective risk

$\bar{I}$ is the level of information upon which the household bases its perceptions

The variable describing the condition of the forest resource, Q, can be defined over a broad range. It is difficult to precisely say what constitutes forest condition, but consider the variable in the limit. At $Q = 0$ there may be no trees at all and therefore very little risk of a wildfire. At the upper limit where Q approaches some maximum level of stand density and fire risk is greater than at $Q = 0$. Alternately, Q may define the household's access to forest resources for recreation through such measures as the distance to recreation opportunities. The closer the household is to forest recreation, the higher the risk of wildfire to the household's community. Forest condition can take on a multitude of definitions, but it is not unreasonable to assume that an increase in forest condition (increased stand density, decreased distance to forest recreation, increased viewshed) increases the risk of wildfire damage to the household's community,

$$(3) \qquad \alpha_Q^C = \frac{\partial \alpha^C}{\partial Q} > 0 .$$

Assume that collective averting behavior has a non-positive impact on community risk,

$$(4) \qquad \alpha_G^C = \frac{\partial \alpha^C}{\partial G} \leq 0 .$$

This is probably an oversimplification since (as discussed in the introduction) the impact of collective averting behavior on fire risk is likely ambiguous. Practices such as prescribed burning may actually increase the risk of wildfire (through an escaped fire) or have no effect at all because of extreme weather conditions that dominate any attempt to alter risk. For the purposes of the model these possibilities will not be considered.

The second source of risk is the risk of damage to the house. This is influenced by the nature of risk to the household's neighborhood, as well as averting activities undertaken by the household to mitigate the probability of damage. In essence this is a quasi-household production framework, where the household takes the subjective community risk and combines it with averting behavior and information to arrive at the subjective risk of damage to their home. Risk of property damage is therefore endogenous. Shogren and Crocker (1991) note that assuming independence between risk and individual actions is too restrictive. Private averting activities, A, are those undertaken by the household and include adopting fire resistant housing materials and clearing fuels from around a structure. I assume that these do not influence the level of community risk ($\alpha_A^C = \frac{\partial \alpha^C}{\partial A} = 0$). The household can install a fire-resistant roof and windows to lessen the risk that fire will damage property, but this does not have any impact on how the household perceives the risk of wildfire in its broader neighborhood. However, it is possible that the averting activities undertaken by a household's neighbors can influence the likelihood of property damage to the household. For example, if a neighbor clears brush from around her house, there is a decreased chance that fire will spread from her house to her neighbor's house. This spatial lag nature of self-protection will not be considered here. The subjective or perceived risk of damage to the household's primary structure is

(5) $\alpha^S = \alpha^S(A, \alpha^C(G, Q, \overline{W}, \bar{I}), \bar{I})$ where

A is private self-protection

$\alpha^C(G, Q, \overline{W}, \bar{I})$ is the perceived or subjective community risk level.

An increase in the subjective assessment of community risk should increase the subjective assessment of damage to the house,

(6) $\alpha^S_{\alpha^C} = \dfrac{\partial \alpha^S}{\partial \alpha^C} > 0$.

For example, say the condition of the forest changes because of an increase in stand density. The household would translate this change into an increase in the perceived level of risk to the overall surrounding community. Because fire is a spatial process and the household is part of the larger community or neighborhood that is subject to the perceived community risk, the house should have an increased probability of damage. In an effort to mitigate the effects of fire risk in the larger community on the household's property, private averting activities are undertaken which decrease the perceived risk of property damage,

(7) $$\alpha^S_A = \frac{\partial \alpha^S}{\partial A} < 0 \,.$$

Note that the bars over the symbols for information and the vector of other determinants of collective risk indicate that they are not choice variables in the maximization problem below. The policy chapter will consider the implications of changing the level of information.

THE EXPECTED UTILITY FRAMEWORK

The standard two state expected utility description of the world, with an "event" state and a "no-event" state, is not adequate to describe housing markets in the presence of wildfire risk. Consider the possible states of the world in this context. The first state is where wildfire risk is present and acknowledged by the household, but there is no realization of a wildfire event. There is no damage to the surrounding forest resource and therefore no reduction in the level of amenities provided by the forest, and no damage to the household's property. In the second state, there is a realization of a wildfire event but no damage to the household's property. There is some level of damage to the forest and therefore the amenity level previously provided by the forest is reduced. The third state of the world is realized when there is a wildfire event that damages not only the forest resource but the household's property as well. Disregarding the unlikely state where wildfire damages the house but leaves the forest resource untouched, a three state model is necessary to consider all possible outcomes.

In developing the model, consider each state in turn. In the no-wildfire state, utility is a function of housing characteristics, the quality of the undamaged forest resource, and a numeraire good.

(8) $v = v(X, \mathbf{Z}, Q)$ where

X is a numeraire good, price normalized to one

Z is a vector of housing characteristics

Q is the condition or quality of the forest resource.

The household can allocate exogenous income between the numeraire good and expenditures on housing represented by the hedonic price function P,

(9) $Y = X + P_H(\mathbf{Z}, A, Q, \alpha^S, \alpha^C)$.

In the wildfire state where the damage is to the community but not the household's property, utility is a function of the numeraire, housing characteristics, and the condition of the forest in the wildfire state

(10) $v^C = v(X, \mathbf{Z}, Q^F)$.

The household's assessment of the probability of this state occurring is α^C, defined in equation (2). The income constraint is

(11) $Y^C = X + P_H(\mathbf{Z}, A, Q, \alpha^S, \alpha^C)$

The wildfire state where both the forest and household property are damaged results in utility

(12) $v^S = v(X, \mathbf{Z}, Q^F)$

with income constraint

(13) $Y^S = X + P_H(\mathbf{Z}, A, Q, \alpha^S, \alpha^C)$.

The subjective probability of this state, α^S, is given in equation (5). The relationship between the incomes in the three states is

(14) $Y^S < Y^C \leq Y$.

Income in the state where there is damage to household property is less than income in the community damage state. This is because the household must expend resources to repair property damage induced by the fire. It is assumed that any damaged property is repaired to maintain the vector **Z** at its pre-fire level (hence no subscript on **Z** in this state). Income in the community damage state is less than or equal to income in the no wildfire state. The difference in income between these two states, if any, could arise from additional expenditures required to travel to alternate recreation sites or from health care costs and lost wage income due to smoke-related illness (these are not treated explicitly in the model).

Private self-protection or averting behavior does not affect the *severity* of damage to the household. This implies that the difference between Y^S and Y^C in equation (14) is unchanged by the level of self-protection undertaken by the household. Changing the level of severity given self-protection would require incorporating a damage function to translate household averting behavior into damages. Only the *probability* of damage to household property is affected by averting effort. If the realization of a wildfire does result in damage to the house, the damage is fixed in severity and amount. This may be overly restrictive but it simplifies the model. The condition of the forest resource in the two fire states is less than the condition in the baseline/non-wildfire state due to fire-inflicted damage

$$(15) \qquad Q^F < Q .$$

The hedonic price function, P_H, increases with the level of housing characteristics, averting qualities of the house, and forest quality, and decreases with the two levels of subjective or perceived risk.

$$(16) \qquad \frac{\partial P_H}{\partial Z_j}, \frac{\partial P_H}{\partial A}, \frac{\partial P_H}{\partial Q} > 0, \; \frac{\partial P_H}{\partial \alpha^S}, \frac{\partial P_H}{\partial \alpha^C} < 0.$$

Of course if Z_j is a "bad", such as age of the house or proximity to a waste incinerator, then $\frac{\partial P_H}{\partial Z_j} < 0$. I assume that the price of housing is a function of the subjective risk levels in the two wildfire states. Buyers and sellers will have assessments of perceived risk based on observations of the prevailing conditions in the market. The hedonic price function represents an envelope of tangencies of the bid and offer curves for various levels of subjective risk. With this specification of the hedonic price function and the definitions of subjective risk in (2) and (5), the response paths of the hedonic given changes in G, A, and Q are somewhat complex and merit a brief discussion. The level of public averting effort indirectly impacts the hedonic through both community risk and structural risk (via the change in community risk).

$$(17) \qquad \frac{dP_H}{dG} = \frac{\partial P_H}{\partial \alpha^S}\alpha^{S}_{\alpha^{C}}\alpha^{C}_{G} + \frac{\partial P_H}{\partial \alpha^C}\alpha^{C}_{G}$$

Since private self-protection efforts are a characteristic of the house, they directly influence the hedonic. Indirect effects are realized through the change in structural risk.

$$(18) \qquad \frac{dP_H}{dA} = \frac{\partial P_H}{\partial A} + \frac{\partial P_H}{\partial \alpha^S}\alpha^{S}_{A}$$

From my assumptions, (17) and (18) should both be positive. The level of forest condition has three pathways for influencing the hedonic price. The first is the direct path that arises since forest condition is a component housing characteristics. Changes in the two risk levels that accompany a change in forest quality comprise the indirect impacts.

$$\text{(19)} \qquad \frac{dP_H}{dQ} = \frac{\partial P_H}{\partial Q} + \frac{\partial P_H}{\partial \alpha^S} \alpha^S_{\alpha C} \alpha^C_Q + \frac{\partial P_H}{\partial \alpha^C} \alpha^C_Q$$

The total derivative of the hedonic with respect to forest condition cannot be signed, as the first term is positive and the second two are negative. This illustrates the conflicting roles that the forest plays in the household's purchasing decision. The forest is a source of both amenities and risk. The empirical application will attempt to separate out these two components of the forest to determine their individual impacts on housing prices.

In all states the utility function increases in the numeraire, "good" household characteristics, and the level of forest quality, and is concave in all of its arguments. Further, X, **Z**, and Q are compliments in preference. That is, increasing the amount of one good increases the marginal utility of the others (Hirshleifer and Riley 1992).

$$\text{(20)} \qquad v_i = \frac{\partial v}{\partial i} > 0 \text{ for } i = X,\ Z_j, \text{ and } Q$$

$$v_{ii} = \frac{\partial^2 v}{\partial i^2} < 0 \text{ for } i = X,\ Z_j, \text{ and } Q$$

$$v_{ik} = \frac{\partial^2 v}{\partial i \partial k} > 0 \text{ for } i, k = X, Z_j, \text{ and } Q.$$

From (14) and (15) the household's utility in the property damage state is less than in the community damage state. Even though the forest resource is impaired in both states, there is less income to allocate to other uses in the property damage state due to repairs. Also, utility in the community damage state is less than utility in the no wildfire state. Combining these relations along with the concavity of utility, Figure 2 illustrates utility surfaces for the three states in relation to the numeraire good.

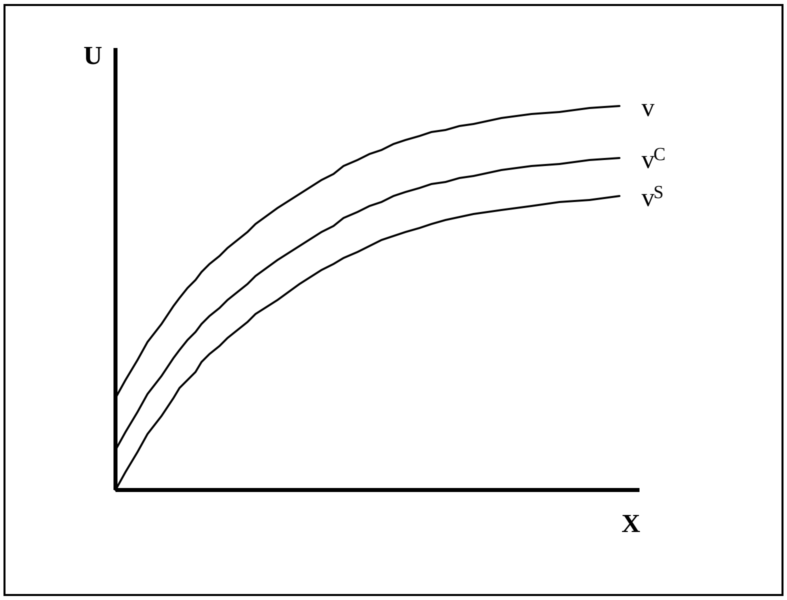

Figure 2: Utility relationships in relation to the numeraire good.

Note that I do not assume state dependent preferences. The levels of utility in the three states (v^S, v^C, and v) will be shorthand for the utility functions evaluated at their respective levels of income and forest quality: $v^S \equiv v(Y^S, Q^f)$, $v^C \equiv v(Y^C, Q^f)$, and $v \equiv v(Y, Q)$. These levels of utility are derived from a single preference function. The type of fire (no fire, fire in the community, and fire that damages both the community and household property) is a "state determining" variable that indicates the level of utility to be "sliced" from the household's single, underlying utility function. This does not preclude the use of the Expected-utility Rule of von-Neumann and Morgenstern since a single cardinal scaling can be used (Hirshleifer and Riley 1992).

The levels of private and collective averting expenditure (A and G) do not explicitly enter into the utility function. Averting activities consist of two components. The first is the actual averting quality itself, such as the fire-resistance of a roof or the increased protection from fire afforded by creating a perimeter of defensible space around a house (by removing highly combustible materials such as trees and brush). These averting qualities are not utility producing, as the households do not have preferences for these apart from their role in risk reduction. The second role of an averting expenditure is as a characteristic of the house. The appearance of a roof and the reduced aesthetic quality from a defensible perimeter are examples. Such characteristics enter utility in all three states. So in the purchase of a house, households have attitudes toward risk that make them care about averting quality and preferences that make them care about appearance and attractiveness. Let one component of the vector **Z**, say Z_A, represent the component of averting activity that is a characteristic of the house and enters in both the hedonic price function and directly in the utility function. The averting quality itself, A, is a component of the hedonic price function and the household's subjective risk, but is not directly utility producing.

The household's problem of maximizing expected utility subject to the budget constraints is

$$\text{(21)} \qquad \underset{X,\mathbf{Z},G,A,Q}{\text{Max}} \; J = E(U) = \alpha^S v\left(X,\mathbf{Z},Q^F\right) + \alpha^C v\left(X,\mathbf{Z},Q^F\right) + (1-\alpha^S-\alpha^C)v(X,\mathbf{Z},Q)$$

$$\text{s.t. } Y = X + P_H(\mathbf{Z},A,Q,\alpha^S,\alpha^C)$$

$$Y^C = X + P_H(\mathbf{Z},A,Q,\alpha^S,\alpha^C)$$

$$Y^S = X + P_H(\mathbf{Z},A,Q,\alpha^S,\alpha^C)\,.$$

Equation (21) is an ex-ante expression the household solves prior to the resolution of uncertainty when the state of nature presents itself. The hedonic price function is always dependent on the baseline level of forest quality, Q, because the household makes its housing decision prior to the possible realization of a wildfire event.

With substitution, the household's problem simplifies to

$$\text{(22)} \qquad \underset{\mathbf{Z},G,A,Q}{\text{Max}}\ J = E(U) = \alpha^S v\left(Y^S - P_H\left(\mathbf{Z}, A, Q, \alpha^S, \alpha^C\right), \mathbf{Z}, Q^F\right)$$

$$+\ \alpha^C v\left(Y^C - P_H\left(\mathbf{Z}, A, Q, \alpha^S, \alpha^C\right), \mathbf{Z}, Q^F\right)$$

$$+\ \left(1 - \alpha^S - \alpha^C\right) v\left(Y - P_H\left(\mathbf{Z}, A, Q, \alpha^S, \alpha^C\right), \mathbf{Z}, Q\right)$$

The first-order conditions of (22) are

$$\text{(23)} \qquad \frac{\partial J}{\partial Z_j} = \alpha^S\left(-v_X^S \frac{\partial P_H}{\partial Z_j} + v_Z^S\right) + \alpha^C\left(-v_X^C \frac{\partial P_H}{\partial Z_j} + v_Z^C\right)$$

$$+\ \left(1 - \alpha^S - \alpha^C\right)\left(-v_X \frac{\partial P_H}{\partial Z_j} + v_Z\right) = 0.$$

$$\text{(24)} \qquad \frac{\partial J}{\partial G} = \alpha^S_{\alpha^C} \alpha^C_G v^S - \alpha^S v_X^S \frac{dP_H}{dG} + \alpha_G^C v^C - \alpha^C v_X^C \frac{dP_H}{dG}$$

$$-\ \left(\alpha^S_{\alpha^C} \alpha^C_G + \alpha^C_G\right) v - \left(1 - \alpha^S - \alpha^C\right) v_X \frac{dP_H}{dG} = 0$$

$$\text{(25)} \qquad \frac{\partial J}{\partial A} = \alpha_A^S v^S - \alpha^S v_X^S \frac{dP_H}{dA} - \alpha^C v_X^C \frac{dP_H}{dA} - \alpha_A^S v - \left(1 - \alpha^S - \alpha^C\right) v_X \frac{dP_H}{dA} = 0$$

$$\text{(26)} \qquad \frac{\partial J}{\partial Q} = \alpha^S_{\alpha^C} \alpha^C_Q v^S + \alpha^S\left\{-v_X^S \frac{dP_H}{dQ} + v^S_{Q^F}\right\} + \alpha_Q^C v^C + \alpha^S\left\{-v_X^C \frac{dP_H}{dQ} + v^C_{Q^F}\right\}$$

$$-\ \left(\alpha^S_{\alpha^C} \alpha^C_Q + \alpha^C_Q\right) v + \alpha^S\left\{-v_X \frac{dP_H}{dQ} + v_Q\right\} = 0.$$

Equations (23) through (26) can be rearranged to show the relationships between the hedonic prices and the marginal rates of substitution.

$$(27)\qquad \frac{\partial P_H}{\partial Z_j} = \frac{\alpha^S v_Z^S + \alpha^C v_Z^C + \left(1-\alpha^S-\alpha^C\right)v_Z}{\alpha^S v_X^S + \alpha^C v_X^C + \left(1-\alpha^S-\alpha^C\right)v_X}$$

$$(28)\qquad \frac{dP_H}{dG} = \alpha_G^C \frac{\alpha^S_{\alpha C}\left(v^S - v\right) + \left(v^C - v\right)}{\alpha^S v_X^S + \alpha^C v_X^C + \left(1-\alpha^S-\alpha^C\right)v_X}$$

$$(29)\qquad \frac{dP_H}{dA} = \frac{\alpha_A^S\left(v^S - v\right)}{\alpha^S v_X^S + \alpha^C v_X^C + \left(1-\alpha^S-\alpha^C\right)v_X}$$

$$(30)\qquad \frac{dP_H}{dQ} = \frac{\alpha^S_{\alpha C}\alpha_Q^C\left(v^S - v\right) + \alpha_Q^C\left(v^C - v\right) + \left[\alpha^S v^S_{Q^F} + \alpha^C v^C_{Q^F} + \left(1-\alpha^S-\alpha^C\right)v_Q\right]}{\alpha^S v_X^S + \alpha^C v_X^C + \left(1-\alpha^S-\alpha^C\right)v_X}$$

The common denominator in equations (27) through (30) is the expected marginal utility of the numeraire good X, which is equal to the expected marginal utility of income (see appendix for derivation). Equation (27) states that the marginal willingness to pay for an incremental unit of housing characteristic Z is equal to the expected marginal rate of substitution between housing characteristics and X. The marginal willingness to pay for collective wildfire protection, expression (28), is the money equivalent of the change in expected damages from the additional unit of collective protection. In (29) the marginal willingness to pay for self-protection is the money equivalent of the expected change in marginal damages from the incremental unit of self-protection.

Equation (30) reveals the complexity of attempting to model how households relate to forest resources. The first two terms in the numerator are the change in expected damages due to a change in forest condition. This represents the impact of a change in forest condition on risk. The next three terms in the numerator constitute the expected marginal utility from an increase in forest condition. Forests present the household with opportunities for recreation and the enjoyment of other amenities, which provide utility. However these same utility-producing qualities also represent a source of increased risk for the household that could result in fire-induced damage that not only reduces the amenity level provided by the forest, but damages household property as well.

INSURANCE

It is appropriate here to make a few comments on insurance. In the theoretical model outlined above, I have not included the opportunity to purchase insurance or considered how insurance could influence the household's choices of location and self-protection. The implications of the theoretical model will not be affected by insurance. If insurance is actuarially fair, then full insurance would make the household indifferent to the state of the world. But there would still be an incentive to self-protect as long as the price of insurance decreased with the level of risk through expenditures on self-protection (Ehrlich and Becker 1972).

IV. DATA, METHODS, AND RESULTS

This chapter begins by discussing the study area that was chosen and the data used to empirically test the hypotheses discussed in the introduction regarding household behavior in the face of wildfire risk. This will be followed by a specification of the estimation procedures used and the presentation of the estimation results. The analysis of the results will be concluded in the policy chapter.

STUDY AREA AND DATA

Several characteristics are important in the selection of the ideal study area to test my hypotheses. First, it must have a residential housing market located near a high-risk fire area (relative to other areas). More specifically this market should be substantial enough (in terms of market size and number of transactions) for collecting adequate data. It should be noted that areas of high fire risk do not often occur near large urban areas. As a result the pool of potential locations for this type of study is relatively narrow and confined to rural or semi-rural areas in the interior west. Next, the area needs to have experienced a large wildfire event to provide an opportunity to examine how risk perceptions respond to fire. Perhaps most importantly the study area needs to provide good access to data. The data requirements for this type of analysis include housing transaction data and information on the prevailing level of fire risk in the area.

The study area chosen for this research is Chelan County, Washington. As outlined below, Chelan fulfills all of the requirements for an ideal study area. Located in central Washington along the Cascade range, Chelan is part of the Wenatchee National Forest. Along with the Wenatchee N.F. the county's other distinguishing physical characteristic is scenic Lake Chelan in the northern part of the county. The area is popular with both retirement and vacation home purchasers and therefore possess a residential housing market substantial enough for the purposes of this analysis. Figures 3 and 4 show the general location of Chelan and the border of the National Forest within the county.

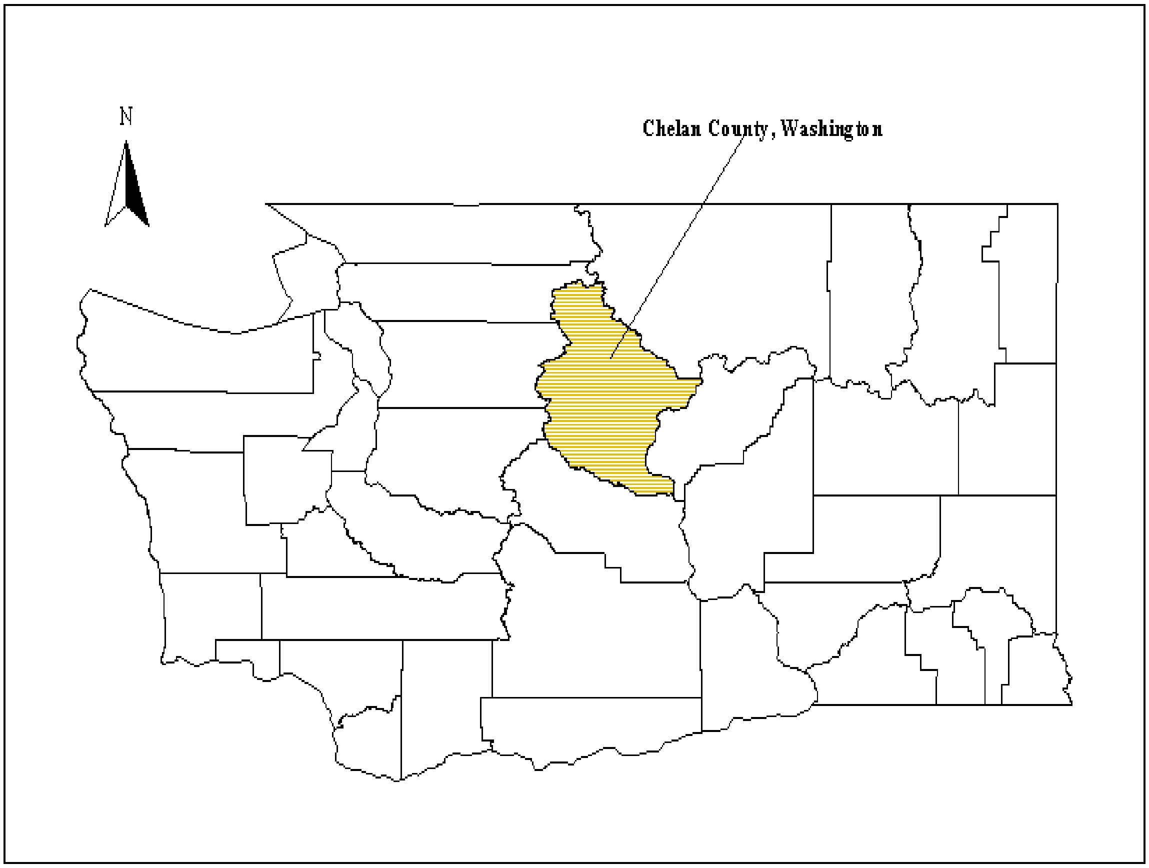

Figure 3: General location of Chelan County in Washington State

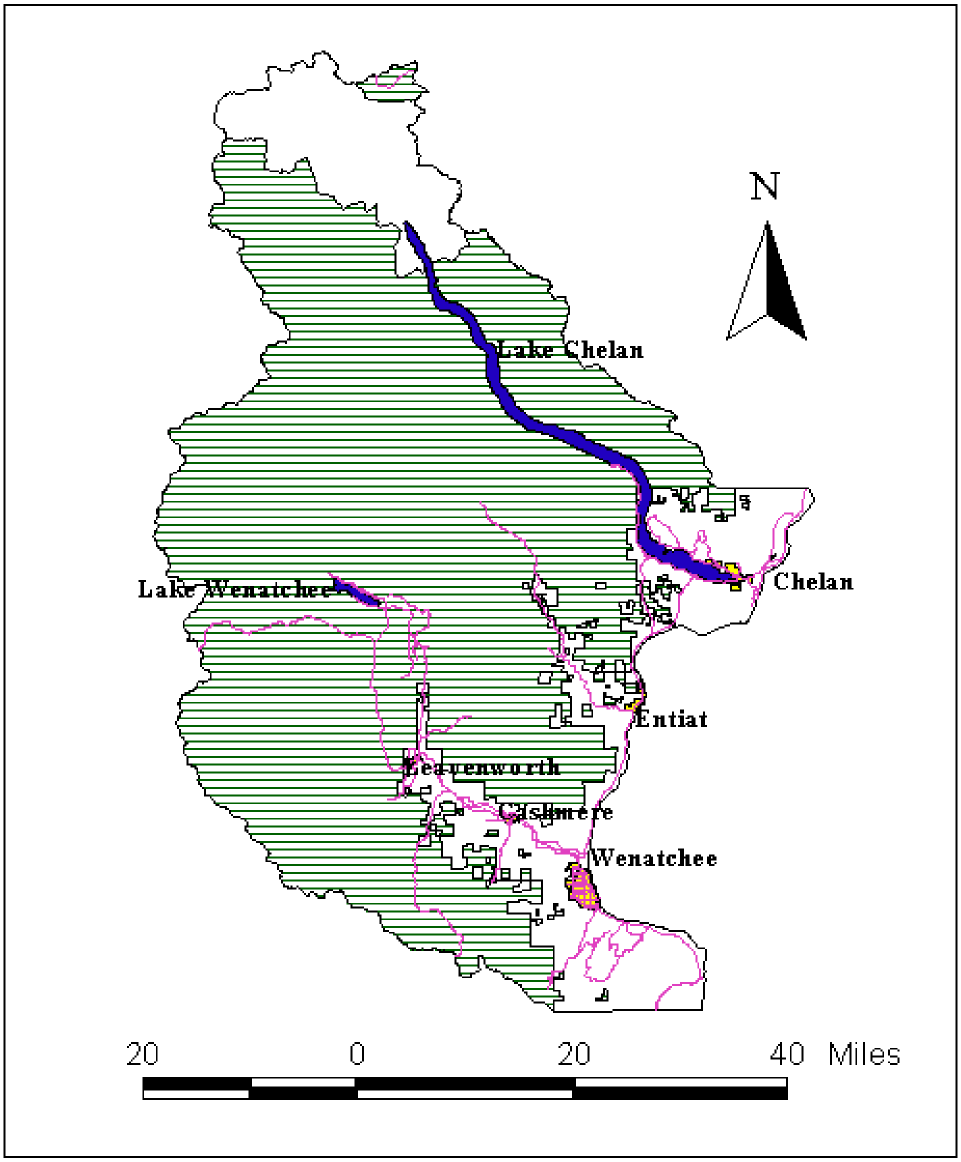

Figure 4: Chelan County and the Wenatchee National Forest

Wildfire is not uncommon for Chelan County, so it provides an area of relatively high risk. Chelan's elevation (as part of the Cascades) makes it a frequent target of lightning strikes. According to Rapp (2002), frequent, low-intensity fires dominated the historic fire regime of the ponderosa pine forests of eastern Washington and Oregon. Plants on the forest floor and smaller, less fire-resistant trees burned but larger trees survived. This regime resulted in an open forest with low fuel levels, where large trees lived for hundreds of years. However, she notes that the fire regime has changed to one of less-frequent, more lethal fires. Fire suppression and exclusion, harvesting of timber, grazing, and the introduction of nonnative plant species have induced an increase in the probability of severe, stand-replacement fires. The result is that many dry, east-side forests have missed between 7 to 10 fire-return intervals. Perhaps Rapp's (2002) most important comment for this study is that forest types characterized by heavy ground fuels and high stand densities are the most common near east-side residential communities.

It is against this backdrop of increased fire risk that the 1994 fires in the Wenatchee National Forest occurred. The fire season of 1994 was especially devastating to the Wenatchee and Chelan County. A set of four distinct fires, which began the last week of July, would burn over 180,000 acres. Suppression costs for the fires were in excess of $69 million, and there were substantial losses of personal property, timber, and tourism revenue. Two of the fires, the Rat Creek and Hatchery would merge into the Hatchery Creek Complex (Carroll et al. 2000). Table 3 lists the size of each fire.

Table 3: Area burned by fire in Chelan County, 1994 (Carroll, et al. 2000)

Fire Name	Acres
Tyee Creek	135,170
Hatchery Creek Complex	43,463
Round Mountain	3,231
Total	181,864

Figure 5 shows the location of the three fires, while Figure 6 illustrates the overlap with the National Forest. Note that two of the three fires, the Tyee Creek and Hatchery Complex, burned over the National Forest boundary.

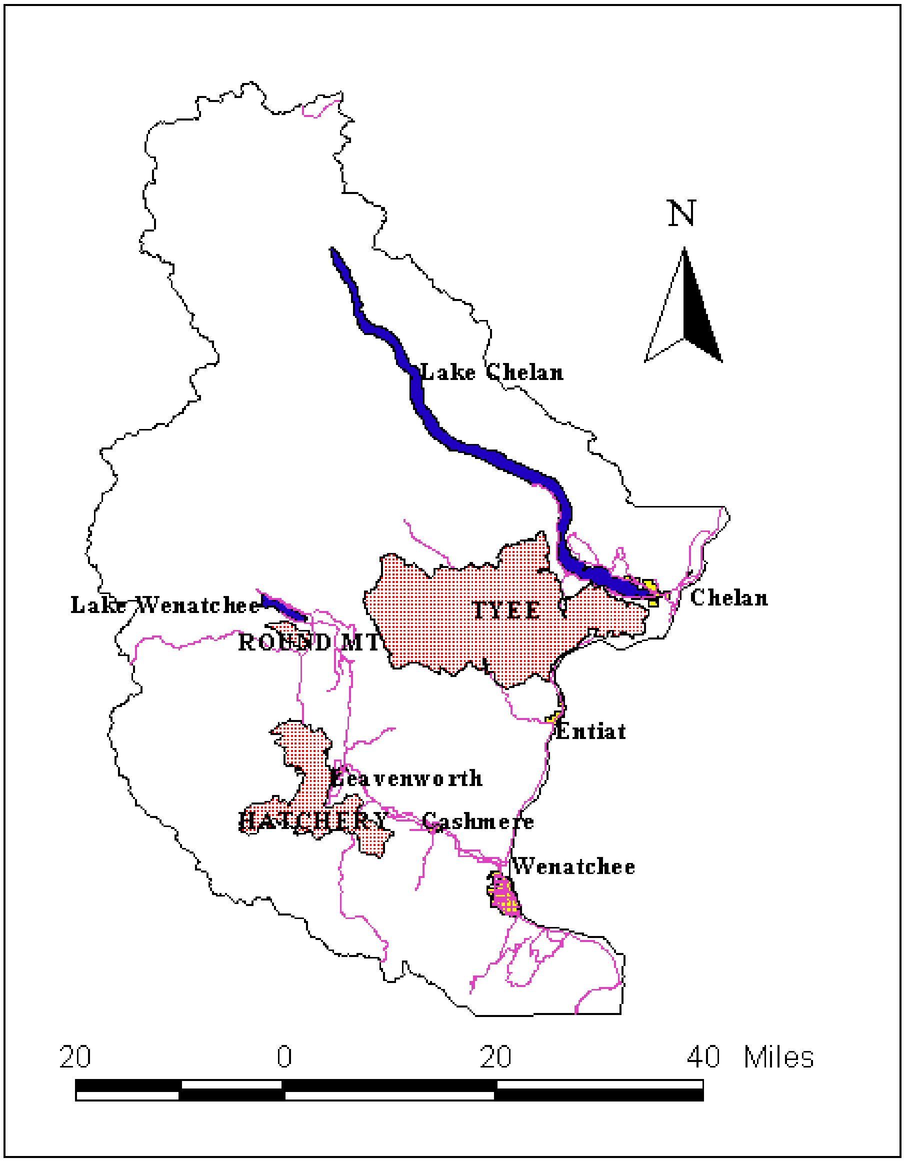

Figure 5: Fire locations

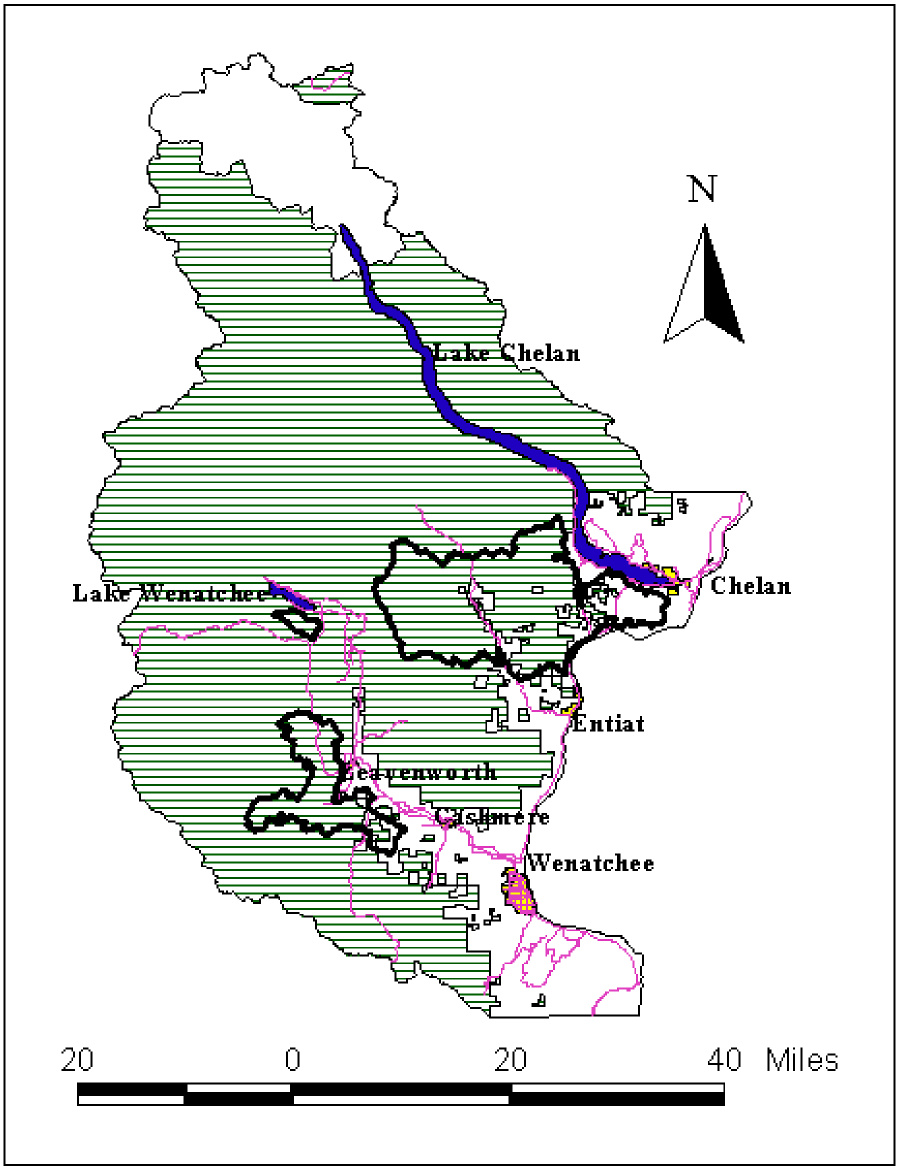

Figure 6: Fire and National Forest boundaries

Housing Data and Neighborhood Data

Housing sales data for 1992 through 1996 were obtained from the Chelan County Assessor's Office. This set included residential transactions (land use codes for single family, vacation & cabin, and all other residential parcels) and a variety of structural variables. To be considered in this analysis, transactions had to include full information on land use, sales price, sales date, year built, type of structure, size of structure, roofing type, and size of parcel. Bare-land transactions, non-arm's length, and other invalid transactions (as identified by the assessor's office) were disregarded. For many transactions where the structure had an age of "0" (sales year minus year of construction) it was not clear if the structure was built on the parcel at the time of sale (the presence of transactions that were improved after the sale and not marked as such was confirmed with the assessor's office). Based on the examination of the bare land values of these transactions in the assessment file and the price of structures with an age of one year, observations with a price less than $60,000 that sold in the year of construction were not included. Leaving these transactions in the data set did not change the fundamental results, however the R^2 values dropped by about one third. Transactions with sales prices under $10,000 were not included. No variable indicating housing quality was available to rationalize these low-price transactions. Further, most were deemed invalid by the assessor's office. Like the parcels with an age of "0", these were not always marked as invalid. Some transactions involved more than one parcel. In these cases only the total sales price for the transaction is entered for each parcel, making it impossible to separate out the consideration given for each individual parcel. If a transaction involved more than one parcel with a residence, it was discarded. In the instances where one parcel had a residence and the other parcel(s) were land only, the number of acres from the bare-land parcels were added to the acres of the residential parcel. Transactions involving lot sizes over 20 acres were also disregarded. This was done to ensure that all transactions were undertaken by buyers for personal, residential use- not for subdividing into smaller parcels or for farming/logging activities, which might represent a different set of preferences. It also reduces the error associated with the neighborhood measures described below, which rely on parcel centroids. Finally, several observations in the extreme west of the county around Stevens Pass and at the northwest tip of Lake Chelan were deemed not part of the same market as the rest of the transactions and not included. A description of each structural and temporal variable constructed from the 1992–1996 sales listing is given below.

Structural

Variable: sales price
Units: dollars
Symbol: *P*; *ln_P* is the natural log of sales price

Variable: lot size
Units: acres
Symbol: *acres*; *ln_acres* is the natural log of lot size

Variable: living space
Units: square feet
Symbol: *sq_ft*; *ln_sq_ft* is the natural log of living space

Variable: age of main structure
Units: years
Symbol: *age*; *ln_age* is the natural log of age
Note: Where construction date was missing in sales records, a best guess of age was made based on the effective age used for assessing structures with unknown build dates, from the most recent county assessment file. For a handful age could be not be found. In order to compute the natural log of age, records with an age of 0 were assigned a value of .5.

Variable: other structure
Units: 1 = yes, 0 = no
Symbol: *oth_struct*
Note: This variable indicates if there is another structure on the property, such as a second house or mobile home, other than the main residence (this does not include a detached garage which is accounted for separately).

Variable: attached garage
Units: 1 = yes, 0 = no
Symbol: *att_gar*

Variable: detached garage
Units: 1 = yes, 0 = no
Symbol: det_gar

Variable: deck or porch
Units: 1 = yes, 0 = no
Symbol: deck_porch

Variable: patio or carport
Units: 1 = yes, 0 = no
Symbol: patio_carport

Variable: unfinished basement
Units: 1 = yes, 0 = no
Symbol: unfin_bsmnt

Variable: finished basement
Units: 1 = yes, 0 = no
Symbol: fin_bsmnt

Variable: class A fire-resistant roof
Units: 1 = yes, 0 = no
Symbol: roof

Variable: fireplace
Units: 1 = yes, 0 = no
Symbol: fireplace

Variable: hot tub
Units: 1 = yes, 0 = no
Symbol: hot_tub

Variable: waterfront
Units: 1 = yes, 0 = no
Symbol: waterfront

Variable: primary mobile
Units: 1 = yes, 0 = no
Symbol: prim_mobile
Note: This variable indicates if a mobile home is the primary structure on the property.

Temporal

> *Variable:* Sales date dummies indicating the half-year that the sale occurred.
> U*nits:* 1 = yes, 0 = no
> *Symbol: sd921, sd922, sd931, sd932, sd941, sd942, sd951, sd952, sd961, sd962*
> *Note:* There are ten total sales date dummies (five years of data with two half-year segments for each year). These will proxy for the general change in the price level within the market. The estimation section will describe how these will be interacted with a subset of the structural and environmental variables.

An expanded note is necessary for the roofing variable. The data from the assessor's office included a variable for 8 different material types that could be used in each structure's roof. Roofing class is measure of fire-resistance, with class A being the highest level. The classification of class A or non-class A roof based on the material categories provided by the assessor's office was confirmed with the Chelan County Fire Marshal. These are summarized in Table 4.

Table 4: Classification of roofing type based on material

Material	**# of obs.**	**Class A (Y/N)**
wood shingle	137	N
wood shake	705	N
clay tile/slate	64	Y
composition shingle/built-up/rock	2,802	Y
composition roll	82	Y
concrete tile	38	Y
other (including masonite)	236	Y
metal	656	Y
Total	**4,720**	

Descriptive statistics of the structural variables are provided in Table 5. Table 6 shows the distribution of observations across the ten time periods proxied by the sales date dummies. Each half-year dummy accounts for roughly eight to eleven percent of the observations.

Table 5: Descriptive statistics of structural variables (n = 4,720)

	Mean	Std Dev	Min	Max
price	114,315.30	64,606.54	10,000.00	975,206.00
lot size	0.694	1.83	0.03	20.00
living area	1,342.08	531.97	96.00	5,586.00
age	33.23	27.49	0	94.00
other structure	0.021	0.143	0	1
attached garage	0.321	0.467	0	1
detached garage	0.217	0.412	0	1
deck/porch	0.464	0.499	0	1
patio/carport	0.319	0.466	0	1
unfinished basement	0.331	0.470	0	1
finished basement	0.230	0.421	0	1
roof type	0.822	0.383	0	1
hot tub	0.020	0.140	0	1
fireplace	0.398	0.490	0	1
waterfront	0.024	0.152	0	1
primary mobile	0.075	0.263	0	1

Table 6: Distribution of observations by sales date dummy variable (n = 4,720)

Sale Date	% of obs.	# of obs.
first half 1992	0.084	398
second half 1992	0.105	495
first half 1993	0.088	415
second half 1993	0.109	516
first half 1994	0.116	547
second half 1994	0.103	484
first half 1995	0.089	421
second half 1995	0.109	515
first half 1996	0.099	465
second half 1996	0.098	464
Total	**1.000**	**4,720**

The Chelan County Assessor's office provided a parcel map for the county. This map was used to spatially reference the sales transactions with Arcview GIS. An attempt was made to geocode the parcel addresses with a variety of methods, including commercial vendors. The rural nature of the county made it impossible to find matches for all of the observations. Many could be matched at no better than the center of the zip code zone. The centroid of each parcel from the parcel map was therefore used as the location for all further GIS work. This may be less than ideal, especially for larger parcels (the larger the parcel, the larger the potential error). However there is a substantial potential for error in geocoding protocols as well, since they rely on linear interpolation of line files such as the TIGER road file for address matching. For parcels that were represented by more than one polygon in the parcel map (and as a result had more than one centroid), the average variable of interest (defined below for vegetation, census variables, and distance to fire and forest boundaries) over all centroids for a parcel was used as the overall parcel measure.

A small number of parcels could not be located on the parcel map. Several of these had very high scores from the geocoding routine in Arcview (at least an 80 matching score) and could be located with this method. The matching score reflects how well an address fits with a candidate location in the TIGER street file. The default value for Arcview to consider a match is 60, but the documentation considers a good match score to be between 75 and 100. Figure 7 illustrates the distribution of observations throughout the county in relation to the fire boundaries. Figures 8-10 show the distribution of observations around the three fires at a finer spatial scale. One-half mile contour lines within a four-mile buffer around the fires are included for perspective.

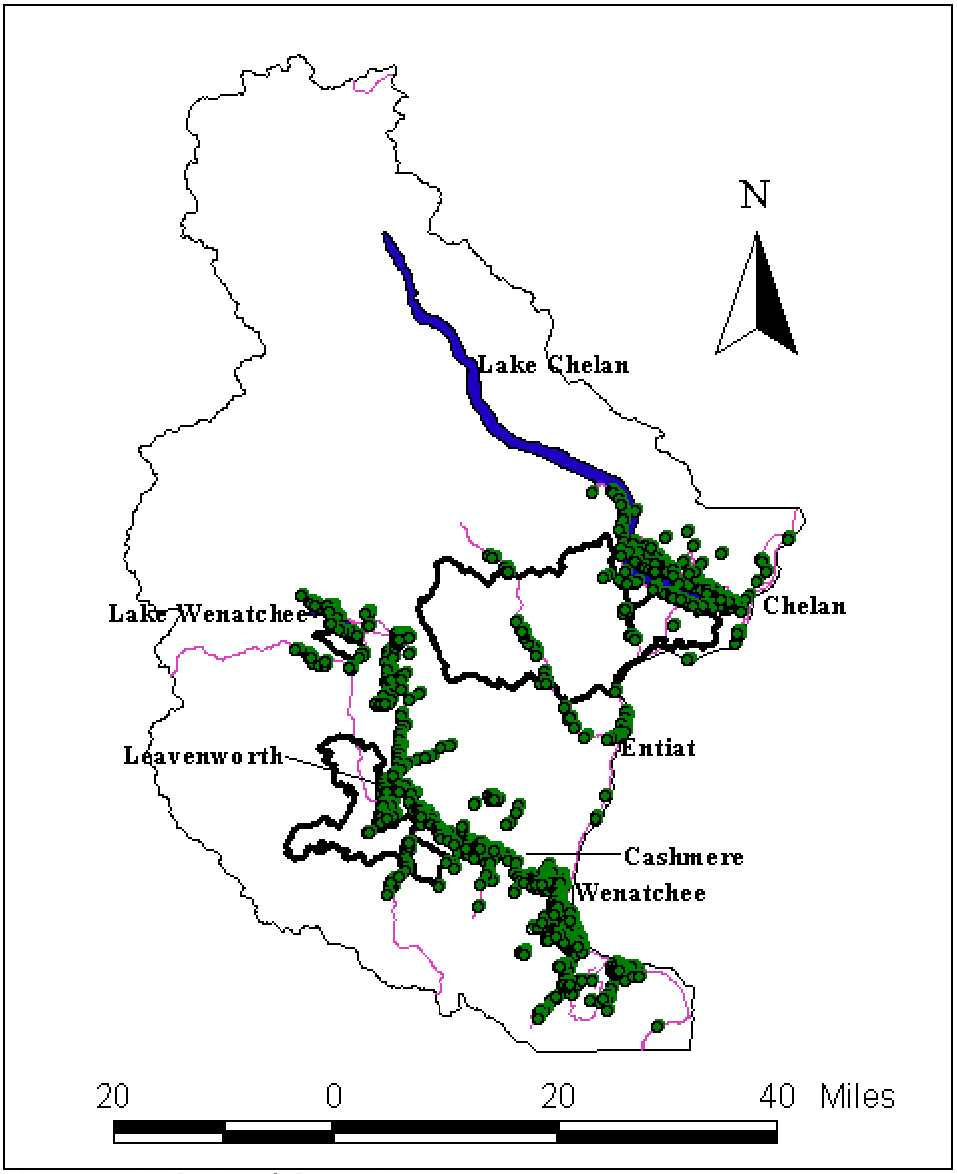

Figure 7: Distribution of observations (n = 4,720)

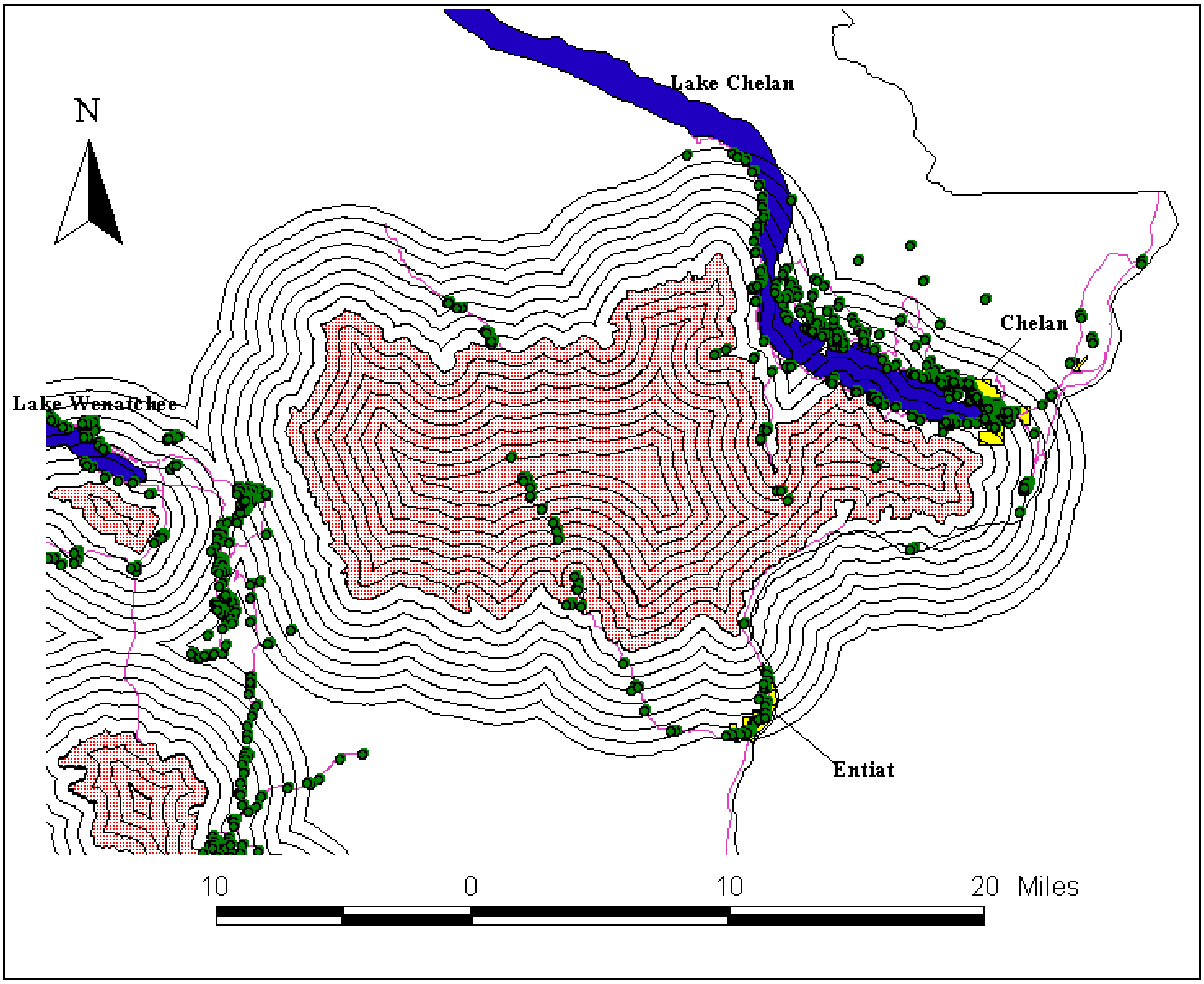

Figure 8: Distribution of observations around the Tyee Creek fire. Note that one-half mile contours from the fire boundary are included.

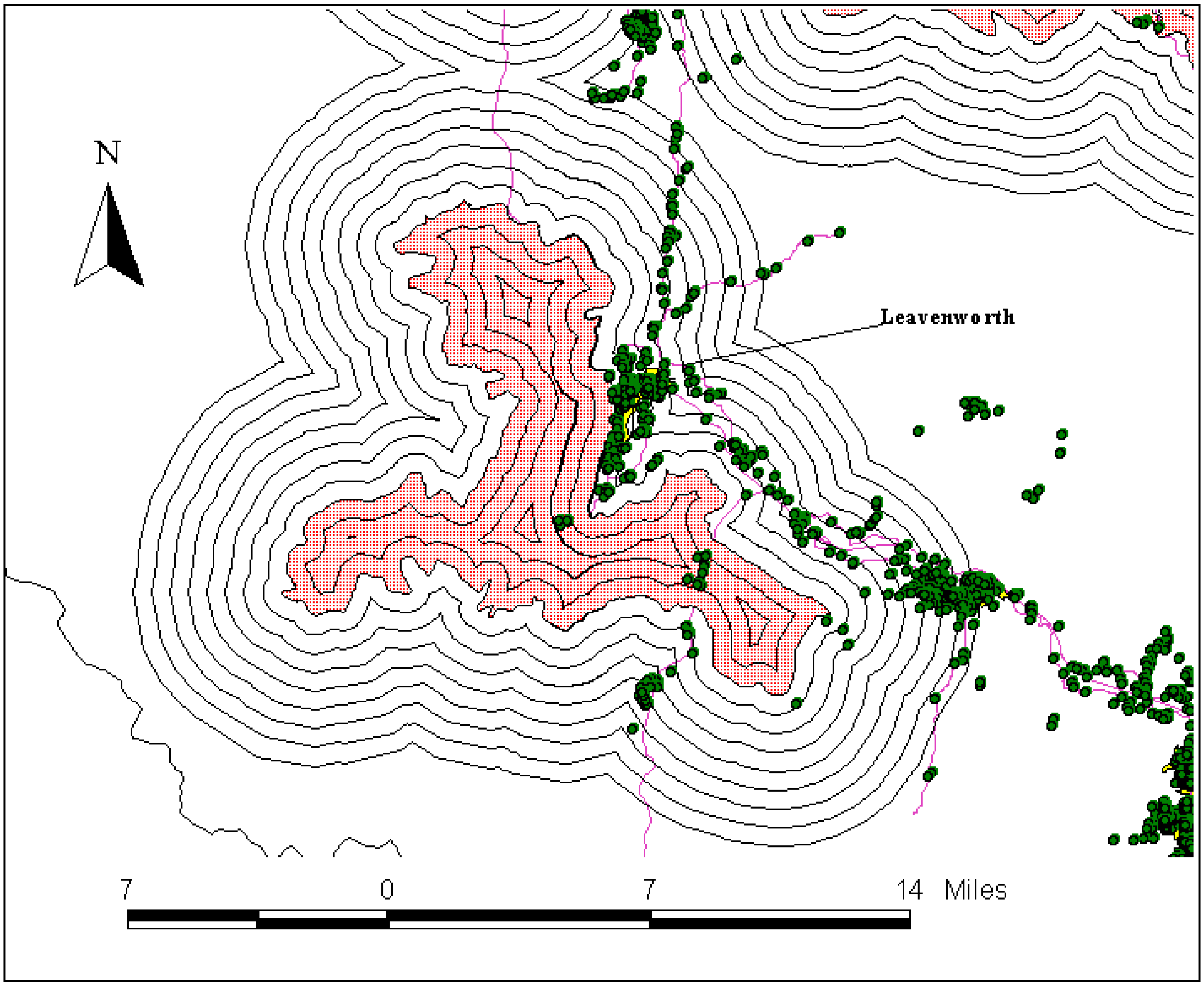

Figure 9: Distribution of observations around the Hatchery fire. Note that one-half mile contours from the fire boundary are included.

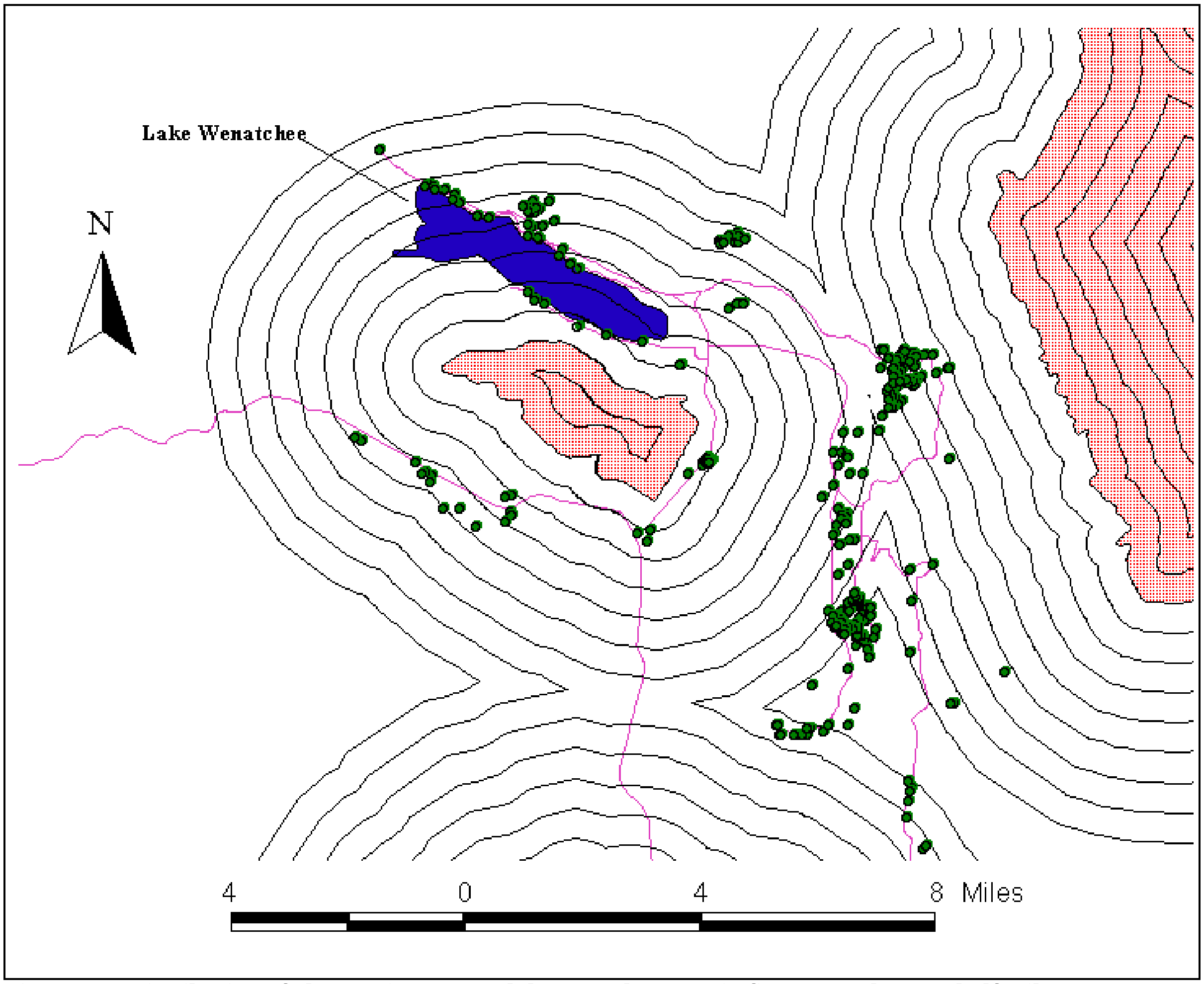

Figure 10: Distribution of observations around the Round Mountain fire. Note that one-half mile contours from the fire boundary are included.

To account for differences in neighborhood or community characteristics, census tract level data for median household income and white population percentage was obtained from the U.S. Census Bureau. Additionally, the kilometers of road in a .40-kilometer (.25 mile) radius around the parcel centroid (from the 2000 TIGER road file for Chelan County) were computed to account for the differing levels of urban development in the data.

Neighborhood

Variable: median household income in the census tract
Units: dollars
Symbol: *med_inc; ln_med_inc* is the log of median household income
Source: 1990 Census, U.S. Census Bureau and the State of Washington

Variable: percent of population that is white in census tract
Units: percent
Symbol: *perc_white*
Source: 1990 Census, U.S. Census Bureau and the State of Washington

Variable: kilometers of road within a .40-kilometer radius
Units: kilometers
Symbol: *road*
Source: 2000 Census, U.S. Census Bureau and the State of Washington

Table 7: Summary statistics of neighborhood variables (n = 4,720)

	Mean	Std Dev	Min	Max
median household income	25,332.18	5,556.84	16,837.00	35,504.00
percent white	92.83	4.21	85.24	97.47
kilometers road	4.87	2.08	0	8.93

Amenity and Risk Variables

As discussed in the chapter outlining the theoretical model, it is very difficult to separate out the impacts of forest amenity and fire risk on housing price. By explicitly controlling for each in the estimating equation I hope to untangle their respective effects.

The measures for amenity in this study will be the distance in kilometers from the parcel centroid to the closest fire boundary and distance in kilometers from the parcel centroid to the national forest boundary. Both measures are necessary to account for the amenity aspect of the forest. The distance to the national forest connotes qualities such as access to recreation and viewshed. Including the distance to the burned area controls explicitly for the change in forest quality due to the fires. This is necessary because even though the fires were very large in area, they did not burn the entire forest. The value of living near an unburned portion of the forest may not change even when the value of living closer to the burned area declines. Observations inside the forest or fire boundaries are assigned zero distances. By including other measures of neighborhood risk such as vegetation type and slope, I hope to allow the distances to the national forest and fire boundaries to "speak" only for the amenity quality of the forest.

Two documents used by fire professions assisted in determining the variables used to control for the level of risk presented by the condition of the forest. *NFPA 1144, Standard for Protection of Life and Property from Wildfire* by the National Fire Protection Association, Inc. (NFPA 2002) and the *Urban-Wildland Interface Code 2000* by the International Fire Code Institute (IFCI 2000) both provide rating systems for assigning risk levels to properties in the urban-wildland interface. The documents contain overlapping information and their rating systems are quite similar. Both rely on measures of access (for fire vehicles), surrounding vegetation, defensible space, roofing type, slope, water source availability, and placement of gas and electric utilities. No data are available for several of these, including the amount of defensible space, water source availability, and placement of utilities. However, as indicated in the description of the structural variables, the roofing type can be inferred from the data received from the assessor's office (the NFPA document notes that class A roofs are tested against severe fire exposures). The *roof* variable (1 = class A, 0 = otherwise) will be used to proxy for the household's averting behavior. For measures of surrounding vegetation, both documents include discussion of the National Fire Danger Rating System (NFDRS) developed by the U.S. Forest Service (Deeming et al.). This system describes the condition of ground fuels, dividing fuels into 20 different models that can be categorized into larger fuel types. This system is very broad, as it is intended to describe fuels for the entire United States, from Florida to Alaska. As a result, not all fuel models will be appropriate for a location. A representation of the NFDRS is shown in Table 8.

Table 8: National Fire Danger Rating System fuel models

	NFDRS Fuel Model	
Grass	A	Western Annuals
	L	Western Perennial
	S	Tundra
	C	Open Pine with Grass
	T	Sagebrush with Grass
	N	Sawgrass
Shrub	B	Mature Brush
	O	High Pocosin
	F	Intermediate Brush
	Q	Alaskan Black Spruce
	D	Southern Rough
Timber	H	Short-Needle Closed (normal dead)
	R	Hardwood Litter (summer)
	U	Western Long-Needle Pine
	P	Southern Long-Needle Pine
	E	Hardwood Litter (fall)
	G	Short-Needle Closed (heavy dead)
Slash	K	Light Slash
	J	Medium Slash
	H	Heavy Slash

The National Land Cover Data (NLCD) provides the link between the household's immediate neighborhood and the fuel model for Washington. This dataset is a product of a joint effort by the U.S. Geological Survey (USGS) and the U.S. Environmental Protection Agency (EPA). The source data is the Multi-Resolution Land Characterization (MRLC) project. Landsat thematic mapping (TM) data from 1986 to 1996 for both leaves on and leaves off (most remote images for Washington State were from the mid 1980s to the early 1990s), terrain elevation data, population and housing density, and land use and land cover data were used to develop a characterization of land cover into 21 classes at a resolution of

30 meters. A disadvantage of this data is the high generality of the classes, however the fine spatial resolution of the data is an advantage in characterizing risk in the area immediately surrounding a house. Table 9 lists the classes of the NLCD.

Table 9: National Land Cover Data classes

	NLCD Classification	
Water	11	Open Water
	12	Perennial Ice/Snow
Developed	21	Low-Intensity Residential
	22	High-Intensity Residential
	23	Commercial/Industrial/Transportation
Barren	31	Bare Rock/Sand/Clay
	32	Quarries/Strip Mines/Gravel Pits
	33	Transitional
Forested Upland	41	Deciduous Forest
	42	Evergreen Forest
	43	Mixed Forest
Shrubland	51	Shrubland
Non-Natural Woody	61	Orchards/Vineyards/Other
Herbaceous Upland	71	Grasslands/Herbaceous
Herbaceous Planted/Cultivated	81	Pasture/Hay
	82	Row Crops
	83	Small Grains
	84	Fallow
	85	Urban/Recreational Grasses
Wetlands	91	Woody Wetlands
	92	Emergent Herbaceous Wetlands

Each thirty-meter pixel in the NLCD grid is assigned a cover type based on its dominant cover, which is described in the NLCD metadata. Upland grasses dominate pixels with cover code 71, grasslands/herbaceous. The herbaceous cover may be under 25 percent but is greater than the combined cover of woody species. Cover code 51 (shrubland) is dominated by shrubland, where shrub canopy can be from 25-100 percent of total. Evergreen cover (code 42) is dominated by trees, where three quarters or greater of these trees keep leaves all year. These three cover codes (71, 51, & 42) correspond roughly to the larger fuel model types in the NFDRS and are the dominant cover types in Chelan County (see Table 12 below). Shrub fuel models are not necessarily more dangerous (higher risk) than grass, and timber fuel models are not always more dangerous than grass or shrub. However a neighborhood measure of the amount of the three NLCD covers allows me to say how much area in that neighborhood is in each of the three broad fuel NLCD fuel classes (and how much in total is fuel).

A neighborhood measure has several advantages. First, it conforms to the NFPA document for describing fuels (light, medium, heavy, or slash) within 300 feet (91 meters) of the structure. Next, the household likely looks at a wider area than just its own parcel and immediate surroundings in assessing risk. This relates to the concept of fire as a spatial process. A household on a low risk parcel surrounded by high-risk parcels probably does not necessarily have an overall low risk level (and vice-versa). A neighborhood-level measure gives a broader indication of risk and proxies for a spatial lag process. Also, since the parcel locations are centroids from the parcel map, a 30-meter grid cell may not be adequate to describe the fuel class (especially for larger parcels). Using a neighborhood will assist in correcting for the error in house location. The neighborhood measures represent the share of pixels in three neighborhood sizes (90 meters, 190 meters, & 510 meters) that are in the three fuel classes. The 190-meter size corresponds roughly to that given in the NFPA document (within about 90 meters of the house in all directions). Alternate sizes, 90 meters and 510 meters, were also used to see how household risk preferences responded to smaller and larger neighborhoods. The 30-meter pixels were resampled to 10 meters to give an equal number of pixels on either side of the center pixel for the 190-meter and 510-meter neighborhoods. An example of neighborhood construction is shown in Figure 11, where the numbers in each pixel (cell) correspond to the NLCD classifications in Table 9.

51	71	42
61	42	42
61	51	71

Figure 11: Example of a land cover neighborhood

If the resolution of Figure 11 is 30 meters, then this represents a 90-meter neighborhood. Three of the pixels are evergreen, two are shrubland, two are grass, and two are orchards/vineyards/other. So a parcel centroid located in the middle pixel has a 90 meter neighborhood (in terms of the three NLCD classes I am concerned with) consisting of a .33 share of evergreen (3/9), a .22 share of shrub (2/9), and a .22 share of grass (2/9).

Slope is a third available variable included in the NFPA and IFCI documents to proxy for the level of risk to the household. Increasing slope corresponds to increased risk because fire burns faster uphill. This seems counterintuitive, but is a result of heat rising. Mosaiced

7.5-minute digital elevation models (DEMs) with 10-meter resolution from the USGS were used to produce a countywide slope grid. Neighborhood measures of slope were developed at the 90-meter, 190-meter, and 510-meter scales. Slope by itself may represent other qualities of the parcel aside from fire risk, such as viewshed. Slope was interacted with the total vegetation (share grass + share shrub + share evergreen) in the appropriate neighborhood to obtain a better measure of risk, *veg_slope*. Summary statistics for the amenity and neighborhood risk measures are given in Table 10. Table 11 presents the share of the county and the 1994 fires in the three cover/fuel classes. Evergreen is the dominant fuel type in the county and not surprisingly, the dominant fuel in the 1994 fires.

Amenity

Variable: distance to the national forest boundary
Units: kilometers
Source: parcel centroid map, national forest coverage
Symbol: *nat_for_dist*
Note: Parcels inside the national forest boundary are assigned a distance of zero.

Variable: distance to the fire boundary
Units: kilometers
Source: parcel centroid map, fire coverage
Symbol: *fire_dist*
Note: Parcels inside the fire boundary are assigned a distance of zero.

Neighborhood Risk

Variable: share of 90-, 190-, and 510-meter neighborhoods in grass cover
Source: National Land Cover Data (NLCD)
Symbol: *grass*

Variable: share of 90-, 190-, and 510-meter neighborhoods in shrub cover
Source: National Land Cover Data (NLCD)
Symbol: *shrub*

Variable: share of 90-, 190-, and 510-meter neighborhoods in evergreen cover
S*ource:* National Land Cover Data (NLCD)
Symbol: egreen

Variable: average slope in 90-, 190-, and 510-meter neighborhoods
S*ource:* USGS digital elevation models
Symbol: slope

Variable: total vegetation in 90-, 190-, and 510-meter neighborhoods
Source: USGS digital elevation models
Symbol: veg
Note: this is the sum of *egreen, shrub, and grass*

Variable: product of total vegetation and average slope in 90-, 190-, and 510-meter neighborhoods
S*ource:* USGS digital elevation models
Symbol: veg_slope
Note: veg_slope = *veg * slope*

Table 10: Summary statistics of amenity and neighborhood risk variables (n = 4,720)

	Mean	Std Dev	Min	Max
distance to national forest boundary	3.64	2.33	0	11.15
distance to fire boundary	13.78	8.35	0	38.16
90-meter neighborhood				
share in grass	0.069	0.180	0	1
share in shrub	0.105	0.199	0	1
share in evergreen	0.082	0.229	0	1
slope	4.52	5.27	0	42.12
190-meter neighborhood				
share in grass	0.069	0.153	0	1
share in shrub	0.101	0.167	0	1
share in evergreen	0.085	0.214	0	1
slope	4.62	4.97	0	37.29
510-meter neighborhood				
share in grass	0.067	0.126	0	0.929
share in shrub	0.097	0.142	0	0.983
share in evergreen	0.089	0.202	0	0.999
slope	5.18	5.04	0.372	32.50

Table 11: Cover types (in percentage of total area) of Chelan County and the 1994 fires

	Evergreen	Shrub	Grass
Chelan County	56.66	16.52	12.00
1994 Fires	62.73	10.65	21.78

Table 12 provides a summary of the data types and sources used for this analysis. For spatial data, information on the original coordinate system, datum, and units are given. Some spatial data were reprojected to a common coordinate system. As a rule, grid data were not reprojected from their original coordinate systems (the exceptions were several DEM grids from UTM zone 11 reprojected to the coordinate system for the majority of the county, UTM zone 10, in order to produce a single elevation model for the county to compute slope).

Table 12: Summary of data types and sources

Sales Transactions & Structural Housing Data for Chelan County, Washington, 1992-1996
Chelan County Assessor's Office, Wenatchee, Washington
Chelan Parcel Map
Chelan County Assessor's Office, Wenatchee, Washington
Washington State Plane North, NAD83, feet
Coverage of the 1994 Wenatchee Fires
U.S. Forest Service, Region 6
UTM Zone 10, NAD27, meters
Median Household Income and Percentage White at the Tract Level from 1990 Census, TIGER Road File from 2000 Census
U.S. Census Bureau and the State of Washington
GCS North American 1983, NAD83, decimal degrees
Digital Elevation Models (DEMs)
U.S. Geological Survey
UTM Zones 10 and 11, NAD27, meters
National Land Cover Data (NLCD)
U.S. Environmental Protection Agency
Albers, NAD83, meters
Various Coverages of Chelan County, including Lakes, Hydrology, National Forest Boundary, Roads, and Cities
Washington Department of Transportation
GCS North American 1983, NAD83, decimal degrees

ESTIMATION

The Difference-In-Difference Estimator

Consider two different locations, one exposed to a natural disaster such as a wildfire and one not exposed. Let P^{td} be the price of a house at time period (t=1 during or after the disaster, t=0 before) in location d (d=1 for the affected location, d=0 for the unaffected) and **X** be a vector of housing characteristics. A before the fire vs. after the fire comparison

$$(31) \qquad E[P^{11}|\mathbf{X}] - E[P^{01}|\mathbf{X}]$$

of prices in the affected area would include not only the impact of the fires on housing prices, but also any other changes in the affected location over that time period (McFadden 2002). Similarly, looking only at the difference in prices between the two locations after the fire

$$(32) \qquad E[P^{11}|\mathbf{X}] - E[P^{10}|\mathbf{X}]$$

would confuse the fire effect and constant differences in the exposed and unexposed areas. This is the primary fault of the PricewaterhouseCoopers (2001) study of how housing markets responded to the 2000 Los Alamos fires. The conditional difference-in-difference estimator

$$(33) \qquad \{E[P^{11}|\mathbf{X}] - E[P^{10}|\mathbf{X}]\} - \{E[P^{01}|\mathbf{X}] - E[P^{00}|\mathbf{X}]\}$$

is a solution that accounts for the differences in the locations as well as changes due to time that are not attributable to the disaster. The first term in brackets is the difference in prices between the locations after the fire while the second bracketed term is the difference in prices between the locations before the fire. By subtracting out the difference in price that prevailed before the fire only the effect of the fire remains. This approach will be used to extract the difference in housing prices attributable to the change in forest amenity due to the fires.

Estimating Equation

With a semi-logarithmic functional form, the general OLS difference-in-difference hedonic estimating equation takes the following form:

$$(34) \qquad \ln P^{td} = \sum_i \beta_i z_i + \upsilon t + \phi d + \delta(t \cdot d)\,.$$

where the z_i are housing characteristics, d is a measure of forest quality, and t is an indicator of whether the house was sold after a fire (= 1 if after, = 0 otherwise). In general $\beta_i > 0$ for all i (with the exception of age and the primary mobile dummy). Assuming that d measures only the amenity aspect of the forest, we would expect $\phi > 0$ so that a house's price increases with forest quality. The outcome of interest is the coefficient on the product of the time and location dummies, δ, which is the equivalent of the conditional difference-in-difference estimator in equation (33)

$$(35) \qquad \{E[P^{11}|\mathbf{X}] - E[P^{10}|\mathbf{X}]\} - \{E[P^{01}|\mathbf{X}] - E[P^{00}|\mathbf{X}]\}$$

$$= \{\ln P^{11} - \ln P^{10}\} - \{\ln P^{01} - \ln P^{00}\}$$

$$= \left\{\left(\sum_i \beta_i z_i + \upsilon + \phi + \delta\right) - \left(\sum_i \beta_i z_i + \upsilon\right)\right\} - \left\{\left(\sum_i \beta_i z_i + \phi\right) - \sum_i \beta_i z_i\right\}$$

$$= \delta .$$

If $\delta < 0$ then we may be able to say that the fire had a negative impact on the market price of a house due to an impaired amenity level.

The variables applied to the difference-in-difference technique are *nat_for_dist* and *fire_dist*, the distances from the parcel centroids to the national forest and fire boundaries which proxy for the level of forest amenity. To account for the possibility that the effect of the three fires is transient and would not be picked up using a simple before and after measure, *nat_for_dist* and *fire_dist* are interacted with the five sales date dummies that represent sales transactions during and after the fire's occurrence (and named *nat_for_dist942*, *fire_dist942*, etc.). Based on the literature review, I expect that *nat_for_dist* and *fire_dist* will both be negative. That is, increasing distance from the national forest and the burned area decreases the price of a house. If the fire impaired the amenity level, the interaction variables for sales dates during and following the fires will be positive. These will adjust the overall levels of *nat_for_dist* and *fire_dist* to reflect the household's new valuation.

The roofing material dummy (*roof*) is interacted with the sales date dummies in the primary estimations (Tables 18-21) and named *roof921, roof922,* etc. The neighborhood risk measures (*egreen, shrub, grass, slope,* and the vegetation-slope interaction term *veg_slope*) are also interacted with all of the sales date dummies (and named *egreen921, shrub922,* etc.) in the auxiliary estimations included in the appendix. These variables are representative of the household's self-protection measures and neighborhood risk from wildfire, so the amenity difference-in-difference logic is not applied to them. The roofing material variable is the proxy for averting behavior (A in the theoretical model), while the neighborhood measures are proxies for the risk associated with the surrounding landscape. I assume that the larger the coefficient on the roof interaction variable, the more the household values self-protection. The larger the coefficients for the neighborhood risk measures, the higher the household's willingness to pay to live in areas of high interface fire risk. The changes in the coefficients of the roofing material variables and neighborhood risk measures over time are important in assessing the evolution of risk perception (the changes in α^C and α^S). This will be discussed further in the next chapter.

A concern regarding the amenity and risk variables is multicollinearity. Table 13 shows the correlation between the distance, vegetation, and slope measures. The correlations between *nat_for_dist, fire_dist,* and *egreen* are moderately high for all three neighborhoods.

Table 13: Correlation summary for amenity and neighborhood risk variables

	nat_for_dist	*fire_dist*	*egreen*	*shrub*	*grass*	*slope*
90m neighborhood						
nat_for_dist	1.0000	0.4282	-0.4717	0.1179	-0.0996	-0.1557
fire_dist		1.0000	-0.3611	-0.0724	-0.2205	-0.2216
egreen			1.0000	-0.0675	-0.0420	0.2224
shrub				1.0000	0.1368	0.3366
grass					1.0000	0.3967
slope						1.0000
190m neighborhood						
nat_for_dist	1.0000	0.4282	-0.5032	0.1208	-0.0858	-0.1767
fire_dist		1.0000	-0.3804	-0.0782	-0.2556	-0.2529
egreen			1.0000	-0.0492	-0.0181	0.2684
shrub				1.0000	0.2805	0.4205
grass					1.0000	0.4941
slope						1.0000
510m neighborhood						
nat_for_dist	1.0000	0.4282	-0.5436	0.1471	-0.0749	-0.2398
fire_dist		1.0000	-0.4080	-0.0563	-0.2872	-0.3194
egreen			1.0000	-0.0391	0.0427	0.3581
shrub				1.0000	0.4446	0.5072
grass					1.0000	0.6405
slope						1.0000

Maddala (1992) notes that high correlations do not necessarily imply a multicollinearity problem. Other tests were used to be certain it posed no problem here. Prior to running the full regressions with interaction variables, a basic model was estimated to get a preliminary look at the results and to compute variance inflation factors (VIFs), a multicollinearity diagnostic. The VIF for regressor *i* is $1/\left(1-R_i^2\right)$ where R_i^2 is the squared multiple correlation coefficient between regressor *i* and all other regressors (Maddala 1992). A VIF in excess of 10 can be an indicator of “damaging” collinearity (Kennedy 1998). Table 14 restates the variable names to assist in interpreting the estimation results. Tables 15-17 show the results of the simple estimations along with the VIFs. No VIF is in excess of 3.4 and most are in the range of 1 to 2. Belsey, Kuh, and Welsch (1980) suggest an additional indicator of possible collinearity. If $\mathbf{K}$ is a matrix of regressors, the condition numbers are the square roots of the ratio of the largest eigenvalue of $\mathbf{K}'\mathbf{K}$ to each individual eigenvalue. Examination of the condition numbers and variance proportions for the simple models of Tables 15-17 revealed possible collinearity between the median household income and the intercept and the percent white and the intercept. Running the models without median household income and percent white did not change the results of the full models beyond very small changes in significance levels. Based on the results of the VIFs and condition number tests, multicollinearity does not appear to be an issue.

Table 14: Summary of variables used in the estimations.

Category	Name	Symbol	Mean
Structural Variables			
	natural log of price	*ln_P*	11.505
	natural log of lot size	*ln_acres*	-1.194
	natural log of living area	*ln_sq_ft*	7.126
	natural log of age	*ln_age*	2.797
	other structure	*oth_struct*	0.021
	attached garage	*att_gar*	0.321
	detached garage	*det_gar*	0.217
	deck/porch	*deck_porch*	0.464
	patio/carport	*patio_carport*	0.319
	unfinished basement	*unfin_bsmnt*	0.331
	finished basement	*fin_bsmnt*	0.230
	roof type	*roof*	0.822
	hot tub	*hot_tub*	0.020
	fireplace	*fireplace*	0.398
	waterfront	*waterfront*	0.024
	primary mobile	*prim_mobile*	0.075
Temporal Variables			
	sale date in first half 1992	*sd921*	0.084
	sale date in second half 1992	*sd922*	0.105
	sale date in first half 1993	*sd931*	0.088
	sale date in second half 1993	*sd932*	0.109
	sale date in first half 1994	*sd941*	0.116
	sale date in second half 1994	*sd942*	0.103
	sale date in first half 1995	*sd951*	0.089
	sale date in second half 1995	*sd952*	0.109
	sale date in first half 1996	*sd961*	0.099
	sale date in second half 1996	*sd962*	0.098
Neighborhood Variables			
	natural log of median household income	*ln_med_inc*	10.116
	percent white	*perc_white*	92.830
	kilometers road	*road*	4.870
Amenity Proxies			
	distance to national forest boundary (km)	*nat_for_dist*	3.640
	distance to fire boundary (km)	*fire_dist*	13.780
Vegetation and Slope: 90-meter neighborhood			
	share in grass	*grass*	0.069
	share in shrub	*shrub*	0.105
	share in evergreen	*egreen*	0.082
	share in total vegetation	*veg*	0.256
	slope	*slope*	4.520
	total vegetation-slope interaction	*veg_slope*	2.155

Table 14 (cont'd): Summary of variables used in the estimations.

Category	Name	Symbol	Mean
Vegetation and Slope: 190-meter neighborhood			
	share in grass	*grass*	0.069
	share in shrub	*shrub*	0.101
	share in evergreen	*egreen*	0.085
	share in total vegetation	*veg*	0.254
	slope	*slope*	4.620
	total vegetation-slope interaction	*veg_slope*	2.183
Vegetation and Slope: 510m neighborhood			
	share in grass	*grass*	0.067
	share in shrub	*shrub*	0.097
	share in evergreen	*egreen*	0.089
	share in total vegetation	*veg*	0.253
	slope	*slope*	5.180
	total vegetation-slope interaction	*veg_slope*	2.445

Table 15: OLS regression results of simple model with VIFs using 90m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Std Err	*t*	p > *t*	VIF
Intercept	6.7327	0.3148	21.3879	0.0000	0.0000 *
ln_acres	0.0686	0.0075	9.1537	0.0000	2.1881 *
ln_sq_ft	0.4906	0.0159	30.9053	0.0000	1.5932 *
ln_age	-0.0602	0.0043	-13.9606	0.0000	1.7843 *
oth_struct	0.1694	0.0357	4.7396	0.0000	1.0294 *
det_gar	0.0887	0.0132	6.7284	0.0000	1.1714 *
att_gar	0.1321	0.0137	9.6189	0.0000	1.6293 *
deck_porch	0.1015	0.0112	9.0852	0.0000	1.2317 *
patio_carport	0.0532	0.0112	4.7689	0.0000	1.0712 *
unfin_bsmnt	0.0667	0.0122	5.4538	0.0000	1.3124 *
fin_bsmnt	0.1866	0.0130	14.3555	0.0000	1.1850 *
fireplace	0.1007	0.0120	8.3710	0.0000	1.3745 *
hot_tub	0.0529	0.0364	1.4548	0.1458	1.0347
waterfront	0.7824	0.0356	21.9761	0.0000	1.1537 *
prim_mobile	-0.5107	0.0214	-23.8744	0.0000	1.2551 *
road	0.0104	0.0043	2.4235	0.0154	3.1667 *
perc_white	0.0022	0.0019	1.1570	0.2473	2.5355
ln_med_inc	0.0954	0.0363	2.6255	0.0087	2.4539 *
sd922	0.0825	0.0233	3.5397	0.0004	2.0205 *
sd931	0.1114	0.0243	4.5871	0.0000	1.8742 *
sd932	0.2261	0.0231	9.7902	0.0000	2.0591 *
sd941	0.2456	0.0228	10.7603	0.0000	2.1166 *
sd942	0.2910	0.0234	12.4258	0.0000	2.0010 *
sd951	0.2932	0.0242	12.1050	0.0000	1.8897 *
sd952	0.3514	0.0231	15.1883	0.0000	2.0625 *
sd961	0.3833	0.0237	16.1743	0.0000	1.9767 *
sd962	0.3862	0.0237	16.3290	0.0000	1.9657 *
roof	-0.0991	0.0143	-6.9216	0.0000	1.1917 *
fire_dist	-0.0046	0.0008	-6.0245	0.0000	1.5850 *
nat_for_dist	-0.0043	0.0030	-1.4404	0.1498	1.8981
egreen	-0.0210	0.0292	-0.7197	0.4717	1.7725
shrub	0.0256	0.0302	0.8464	0.3974	1.4260
grass	0.0576	0.0329	1.7482	0.0805	1.3871 **
slope	0.0013	0.0012	1.0461	0.2956	1.6929

note: * denotes significance at 5%, ** denotes significance at 10%

n = 4,720

R^2 = .6102

adjusted R^2 = .6074

Table 16: OLS regression results of simple model with VIFs using 190m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Std Err	*t*	p > *t*	VIF
Intercept	6.7610	0.3169	21.3366	0.0000	0.0000 *
ln_acres	0.0689	0.0075	9.1608	0.0000	2.2075 *
ln_sq_ft	0.4889	0.0159	30.6746	0.0000	1.6056 *
ln_age	-0.0603	0.0043	-13.9548	0.0000	1.7899 *
oth_struct	0.1675	0.0357	4.6859	0.0000	1.0294 *
det_gar	0.0887	0.0132	6.7194	0.0000	1.1730 *
att_gar	0.1319	0.0137	9.5926	0.0000	1.6314 *
deck_porch	0.1023	0.0112	9.1332	0.0000	1.2352 *
patio_carport	0.0527	0.0112	4.7178	0.0000	1.0721 *
unfin_bsmnt	0.0665	0.0122	5.4352	0.0000	1.3135 *
fin_bsmnt	0.1857	0.0130	14.2699	0.0000	1.1874 *
fireplace	0.1001	0.0120	8.3212	0.0000	1.3747 *
hot_tub	0.0537	0.0364	1.4752	0.1402	1.0355
waterfront	0.7802	0.0356	21.8849	0.0000	1.1563 *
prim_mobile	-0.5080	0.0214	-23.7452	0.0000	1.2545 *
road	0.0094	0.0044	2.1650	0.0304	3.2649 *
perc_white	0.0022	0.0019	1.1414	0.2538	2.5614
ln_med_inc	0.0950	0.0366	2.5992	0.0094	2.4850 *
sd922	0.0826	0.0233	3.5428	0.0004	2.0235 *
sd931	0.1105	0.0243	4.5478	0.0000	1.8743 *
sd932	0.2260	0.0231	9.7844	0.0000	2.0591 *
sd941	0.2455	0.0228	10.7510	0.0000	2.1168 *
sd942	0.2909	0.0234	12.4185	0.0000	2.0009 *
sd951	0.2923	0.0242	12.0676	0.0000	1.8890 *
sd952	0.3510	0.0231	15.1673	0.0000	2.0624 *
sd961	0.3830	0.0237	16.1607	0.0000	1.9767 *
sd962	0.3864	0.0237	16.3329	0.0000	1.9660 *
roof	-0.0998	0.0143	-6.9680	0.0000	1.1913 *
fire_dist	-0.0047	0.0008	-6.1142	0.0000	1.6073 *
nat_for_dist	-0.0046	0.0030	-1.5323	0.1255	1.9416
egreen	-0.0423	0.0326	-1.2954	0.1953	1.9308
shrub	0.0102	0.0381	0.2669	0.7895	1.6027
grass	0.0257	0.0411	0.6257	0.5316	1.5626
slope	0.0020	0.0014	1.3956	0.1629	2.0004

note: * denotes significance at 5%, ** denotes significance at 10%

n = 4,720

R^2 = .6100

adjusted R^2 = .6073

Table 17: OLS regression results of simple model with VIFs using 510m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Std Err	*t*	p > *t*	VIF
Intercept	6.7732	0.3211	21.0965	0.0000	0.0000 *
ln_acres	0.0736	0.0076	9.7208	0.0000	2.2303 *
ln_sq_ft	0.4900	0.0160	30.5992	0.0000	1.6198 *
ln_age	-0.0614	0.0043	-14.2368	0.0000	1.7851 *
oth_struct	0.1637	0.0358	4.5790	0.0000	1.0293 *
det_gar	0.0854	0.0132	6.4650	0.0000	1.1733 *
att_gar	0.1294	0.0137	9.4195	0.0000	1.6280 *
deck_porch	0.1045	0.0112	9.3428	0.0000	1.2322 *
patio_carport	0.0518	0.0112	4.6393	0.0000	1.0712 *
unfin_bsmnt	0.0673	0.0122	5.4986	0.0000	1.3136 *
fin_bsmnt	0.1882	0.0130	14.4839	0.0000	1.1830 *
fireplace	0.0999	0.0120	8.3099	0.0000	1.3719 *
hot_tub	0.0552	0.0364	1.5169	0.1294	1.0351
waterfront	0.7705	0.0358	21.5032	0.0000	1.1675 *
prim_mobile	-0.5059	0.0214	-23.6774	0.0000	1.2511 *
road	0.0061	0.0044	1.3799	0.1677	3.3806
perc_white	0.0008	0.0019	0.4251	0.6708	2.5717
ln_med_inc	0.1106	0.0370	2.9871	0.0028	2.5478 *
sd922	0.0826	0.0233	3.5409	0.0004	2.0220 *
sd931	0.1113	0.0243	4.5844	0.0000	1.8731 *
sd932	0.2261	0.0231	9.7852	0.0000	2.0591 *
sd941	0.2456	0.0228	10.7520	0.0000	2.1168 *
sd942	0.2908	0.0234	12.4109	0.0000	2.0005 *
sd951	0.2918	0.0242	12.0428	0.0000	1.8890 *
sd952	0.3509	0.0231	15.1591	0.0000	2.0625 *
sd961	0.3842	0.0237	16.2044	0.0000	1.9766 *
sd962	0.3869	0.0237	16.3504	0.0000	1.9657 *
roof	-0.1019	0.0143	-7.1150	0.0000	1.1911 *
fire_dist	-0.0048	0.0008	-6.2485	0.0000	1.6309 *
nat_for_dist	-0.0055	0.0031	-1.7803	0.0751	2.0304 **
egreen	-0.0331	0.0371	-0.8918	0.3725	2.2272
shrub	0.0101	0.0488	0.2077	0.8355	1.9008
grass	0.0360	0.0567	0.6357	0.5250	2.0107
slope	-0.0021	0.0017	-1.2706	0.2039	2.8547

note: * denotes significance at 5%, ** denotes significance at 10%

n = 4,720

R^2 = .6098

adjusted R^2 = .6071

An interesting outcome of these simple estimations is that the *roof* and *fire_dist* have significant impacts on the log of price. A class A roof detracts from the price of a house while households are willing to pay a premium to live near the burned area. As the full models will show, the impacts of these variables are not constant but vary over time.

RESULTS

Ordinary least squares regression results of the full model with interaction terms are presented in Tables 18–21. The first three estimations feature the vegetation and slope variables for the 90-, 190-, and 510-meter neighborhoods. The final estimation omits the vegetation and slope measures entirely. A potential problem with spatial data is a non-constant error variance, or heteroskedasticity. In the presence of heteroskedasticity, the coefficient estimates are unbiased but the standard errors of the estimates are biased (Maddala 1992). Any inference based on the biased standard errors will be incorrect. Visual inspection of the squared residuals from the simple models plotted against the vegetation measures suggested possible heteroskedasticity. The SAS command *ACOV* was used to generate the heteroskedasticity consistent covariance matrix (HCCM),

$$\text{(36)} \qquad \text{HCCM} = \left(\mathbf{K'K}\right)^{-1}\mathbf{K'}\left[\text{diag}\left(\text{ee}'\right)\right]\mathbf{K}\left(\mathbf{K'K}\right)^{-1}$$

where **K** is the matrix of regressors and e is the vector of residuals from the OLS regression. This estimator is useful because that inference can be performed without specifying the actual form of heteroskedasticity (Greene 2000). White (1980) explains that the statistic for testing the significance of each regressor using the HCCM is distributed χ^2 with 1 degree of freedom, which is exactly the square of the asymptotic *t* statistic. The vector of asymptotic standard errors using the HCCM

(37) $\sqrt{diag(\mathrm{HCCM})}$

was used to derive the χ^2 test statistics,

(38) $\chi_i^2 = \left(\dfrac{\beta_i}{\mathrm{ASE}_i} \right)^2$

where β_i is the OLS coefficient estimate of the ith regressor and ASE_i is the associated asymptotic standard error from (37).

Table 18: OLS regression results of model using 90m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.6754	0.2974	503.9329	0.0000*
ln_acres	0.0656	0.0109	36.5636	0.0000*
ln_sq_ft	0.4914	0.0187	692.7452	0.0000*
ln_age	-0.0591	0.0045	171.7325	0.0000*
oth_struct	0.1713	0.0530	10.4333	0.0012*
att_gar	0.1325	0.0120	122.2338	0.0000*
det_gar	0.0860	0.0134	41.1173	0.0000*
deck_porch	0.1024	0.0114	79.9637	0.0000*
patio_carport	0.0535	0.0106	25.3987	0.0000*
unfin_bsmnt	0.0655	0.0109	35.7593	0.0000*
fin_bsmnt	0.1882	0.0114	273.9847	0.0000*
hot_tub	0.0577	0.0490	1.3887	0.2386
fireplace	0.1018	0.0106	92.2868	0.0000*
waterfront	0.7861	0.0566	193.0102	0.0000*
prim_mobile	-0.5059	0.0326	240.3612	0.0000*
perc_white	0.0019	0.0018	1.0273	0.3108
ln_med_inc	0.1096	0.0311	12.4239	0.0004*
road	0.0072	0.0047	2.3442	0.1257
sd922	0.0687	0.0487	1.9920	0.1581
sd931	0.1563	0.0453	11.9106	0.0006*
sd932	0.1946	0.0475	16.7875	0.0000*
sd941	0.2392	0.0420	32.4159	0.0000*
sd942	0.2797	0.0616	20.5894	0.0000*
sd951	0.1582	0.0740	4.5677	0.0326*
sd952	0.2551	0.0633	16.2166	0.0001*
sd961	0.2770	0.0749	13.6810	0.0002*
sd962	0.4119	0.0522	62.2136	0.0000*
roof921	-0.1356	0.0408	11.0275	0.0009*
roof922	-0.1166	0.0391	8.8885	0.0029*
roof931	-0.1926	0.0383	25.3396	0.0000*
roof932	-0.0944	0.0370	6.5028	0.0108*
roof941	-0.1279	0.0315	16.4830	0.0000*
roof942	-0.0871	0.0360	5.8618	0.0155*
roof951	-0.1003	0.0433	5.3650	0.0205*
roof952	-0.0229	0.0343	0.4466	0.5039
roof961	0.0261	0.0492	0.2824	0.5952
roof962	-0.1364	0.0253	28.9683	0.0000*
nat_for_dist	-0.0064	0.0045	1.9770	0.1597
nat_for_dist942	-0.0065	0.0082	0.6354	0.4254
nat_for_dist951	0.0076	0.0116	0.4231	0.5154
nat_for_dist952	0.0025	0.0085	0.0844	0.7714
nat_for_dist961	0.0162	0.0088	3.3942	0.0654**

Table 18 (cont'd): OLS regression results of model using 90m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
nat_for_dist962	0.0082	0.0088	0.8824	0.3476
fire_dist	-0.0043	0.0011	15.3103	0.0001*
fire_dist942	-0.0003	0.0022	0.0205	0.8860
fire_dist951	0.0056	0.0032	3.0625	0.0801**
fire_dist952	-0.0004	0.0024	0.0216	0.8831
fire_dist961	-0.0062	0.0024	6.9095	0.0086*
fire_dist962	-0.0041	0.0022	3.3990	0.0652**
egreen	-0.0732	0.0407	3.2286	0.0724**
shrub	-0.0241	0.0371	0.4205	0.5167
grass	-0.0133	0.0441	0.0912	0.7627
slope	-0.0044	0.0027	2.7033	0.1001
veg_slope	0.0094	0.0036	6.7788	0.0092*

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720

R^2 = .6147

adjusted R^2 = .6103

Table 19: OLS regression results of model using 190m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.7085	0.3010	496.7634	0.0000*
ln_acres	0.0662	0.0110	36.1300	0.0000*
ln_sq_ft	0.4904	0.0188	682.8511	0.0000*
ln_age	-0.0591	0.0045	170.3550	0.0000*
oth_struct	0.1678	0.0533	9.9259	0.0016*
att_gar	0.1318	0.0119	121.8438	0.0000*
det_gar	0.0863	0.0134	41.2514	0.0000*
deck_porch	0.1032	0.0115	80.0248	0.0000*
patio_carport	0.0530	0.0106	24.8128	0.0000*
unfin_bsmnt	0.0659	0.0109	36.2445	0.0000*
fin_bsmnt	0.1867	0.0114	269.7182	0.0000*
hot_tub	0.0581	0.0492	1.3959	0.2374
fireplace	0.1011	0.0106	91.0208	0.0000*
waterfront	0.7828	0.0566	191.2188	0.0000*
prim_mobile	-0.5053	0.0327	238.8582	0.0000*
perc_white	0.0018	0.0018	0.9947	0.3186
ln_med_inc	0.1077	0.0314	11.7387	0.0006*
road	0.0068	0.0047	2.0306	0.1542
sd922	0.0690	0.0485	2.0238	0.1548
sd931	0.1566	0.0449	12.1423	0.0005*
sd932	0.1954	0.0474	17.0180	0.0000*
sd941	0.2420	0.0419	33.3753	0.0000*
sd942	0.2781	0.0617	20.2974	0.0000*
sd951	0.1570	0.0737	4.5346	0.0332*
sd952	0.2565	0.0633	16.4391	0.0001*
sd961	0.2763	0.0749	13.6053	0.0002*
sd962	0.4127	0.0523	62.1712	0.0000*
roof921	-0.1356	0.0407	11.1013	0.0009*
roof922	-0.1171	0.0391	8.9854	0.0027*
roof931	-0.1941	0.0381	25.9424	0.0000*
roof932	-0.0957	0.0370	6.6792	0.0098*
roof941	-0.1303	0.0315	17.1164	0.0000*
roof942	-0.0861	0.0361	5.6776	0.0172*
roof951	-0.0999	0.0430	5.3907	0.0202*
roof952	-0.0248	0.0342	0.5247	0.4688
roof961	0.0265	0.0493	0.2881	0.5915
roof962	-0.1374	0.0256	28.7998	0.0000*
nat_for_dist	-0.0072	0.0045	2.4952	0.1142
nat_for_dist942	-0.0063	0.0081	0.5952	0.4404
nat_for_dist951	0.0076	0.0116	0.4264	0.5137
nat_for_dist952	0.0028	0.0085	0.1047	0.7463
nat_for_dist961	0.0170	0.0088	3.7255	0.0536**

Table 19 (cont'd): OLS regression results of model using 190m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
nat_for_dist962	0.0085	0.0088	0.9410	0.3320
fire_dist	-0.0043	0.0011	15.1467	0.0001*
fire_dist942	-0.0003	0.0022	0.0216	0.8831
fire_dist951	0.0057	0.0032	3.1511	0.0759**
fire_dist952	-0.0004	0.0024	0.0273	0.8688
fire_dist961	-0.0064	0.0024	7.3522	0.0067*
fire_dist962	-0.0042	0.0023	3.4454	0.0634**
egreen	-0.0847	0.0463	3.3527	0.0671**
shrub	-0.0257	0.0467	0.3027	0.5822
grass	-0.0336	0.0590	0.3255	0.5683
slope	-0.0026	0.0031	0.7122	0.3987
veg_slope	0.0075	0.0044	2.8779	0.0898**

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720

R^2 = .6142

adjusted R^2 = .6098

Table 20: OLS regression results of model using 510m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.7448	0.3080	479.5475	0.0000*
ln_acres	0.0715	0.0111	41.4751	0.0000*
ln_sq_ft	0.4915	0.0188	681.0870	0.0000*
ln_age	-0.0603	0.0045	177.5962	0.0000*
oth_struct	0.1614	0.0531	9.2227	0.0024*
att_gar	0.1292	0.0120	116.5154	0.0000*
det_gar	0.0838	0.0134	38.8698	0.0000*
deck_porch	0.1051	0.0115	83.4192	0.0000*
patio_carport	0.0524	0.0107	24.1102	0.0000*
unfin_bsmnt	0.0670	0.0109	37.5415	0.0000*
fin_bsmnt	0.1889	0.0113	277.2589	0.0000*
hot_tub	0.0603	0.0494	1.4903	0.2222
fireplace	0.1007	0.0106	90.8097	0.0000*
waterfront	0.7707	0.0570	182.8819	0.0000*
prim_mobile	-0.5055	0.0327	239.4633	0.0000*
perc_white	0.0005	0.0019	0.0639	0.8005
ln_med_inc	0.1196	0.0326	13.5024	0.0002*
road	0.0045	0.0048	0.8687	0.3513
sd922	0.0677	0.0489	1.9167	0.1662
sd931	0.1590	0.0450	12.4927	0.0004*
sd932	0.1951	0.0475	16.8727	0.0000*
sd941	0.2431	0.0422	33.1974	0.0000*
sd942	0.2783	0.0623	19.9763	0.0000*
sd951	0.1634	0.0746	4.8027	0.0284*
sd952	0.2572	0.0633	16.5103	0.0000*
sd961	0.2748	0.0753	13.3312	0.0003*
sd962	0.4136	0.0527	61.5199	0.0000*
roof921	-0.1373	0.0410	11.1918	0.0008*
roof922	-0.1168	0.0392	8.8607	0.0029*
roof931	-0.1967	0.0379	26.9089	0.0000*
roof932	-0.0967	0.0370	6.8487	0.0089*
roof941	-0.1320	0.0316	17.3835	0.0000*
roof942	-0.0891	0.0364	5.9889	0.0144*
roof951	-0.1046	0.0435	5.7942	0.0161*
roof952	-0.0256	0.0341	0.5627	0.4532
roof961	0.0258	0.0497	0.2691	0.6040
roof962	-0.1427	0.0257	30.7495	0.0000*
nat_for_dist	-0.0085	0.0046	3.4864	0.0619**
nat_for_dist942	-0.0064	0.0082	0.6081	0.4355
nat_for_dist951	0.0076	0.0116	0.4306	0.5117
nat_for_dist952	0.0025	0.0085	0.0883	0.7663
nat_for_dist961	0.0177	0.0088	4.0973	0.0430*

Table 20 (cont'd): OLS regression results of model using 510m neighborhood where vegetation and slope variables are not interacted with sale date. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
nat_for_dist962	0.0095	0.0087	1.1815	0.2771
fire_dist	-0.0043	0.0012	13.8944	0.0002*
fire_dist942	-0.0002	0.0022	0.0063	0.9368
fire_dist951	0.0055	0.0032	2.9317	0.0869**
fire_dist952	-0.0004	0.0024	0.0253	0.8736
fire_dist961	-0.0065	0.0024	7.4628	0.0063*
fire_dist962	-0.0042	0.0023	3.5595	0.0592**
egreen	-0.0536	0.0537	0.9985	0.3177
shrub	-0.0035	0.0583	0.0036	0.9523
grass	0.0013	0.0817	0.0003	0.9872
slope	-0.0044	0.0035	1.5489	0.2133
veg_slope	0.0036	0.0051	0.4939	0.4822

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720

R^2 = .6137

adjusted R^2 = .6098

Table 21: OLS regression results of model excluding vegetation and slope variables. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.7164	0.2900	536.3509	0.0000*
ln_acres	0.0694	0.0103	45.6251	0.0000*
ln_sq_ft	0.4955	0.0183	733.6253	0.0000*
ln_age	-0.0594	0.0044	179.7129	0.0000*
oth_struct	0.1619	0.0530	9.3352	0.0022*
att_gar	0.1322	0.0119	123.7304	0.0000*
det_gar	0.0858	0.0134	41.1432	0.0000*
deck_porch	0.1030	0.0114	81.6045	0.0000*
patio_carport	0.0523	0.0107	24.1083	0.0000*
unfin_bsmnt	0.0677	0.0109	38.5013	0.0000*
fin_bsmnt	0.1891	0.0113	279.4422	0.0000*
hot_tub	0.0608	0.0491	1.5302	0.2161
fireplace	0.1006	0.0105	91.2967	0.0000*
waterfront	0.7727	0.0567	185.7318	0.0000*
prim_mobile	-0.5047	0.0327	238.1577	0.0000*
perc_white	0.0008	0.0018	0.1802	0.6712
ln_med_inc	0.1122	0.0307	13.3576	0.0003*
road	0.0068	0.0047	2.1099	0.1463
sd922	0.0684	0.0485	1.9901	0.1583
sd931	0.1597	0.0449	12.6705	0.0004*
sd932	0.1947	0.0473	16.9257	0.0000*
sd941	0.2426	0.0420	33.3903	0.0000*
sd942	0.2740	0.0619	19.5649	0.0000*
sd951	0.1598	0.0737	4.7027	0.0301*
sd952	0.2560	0.0631	16.4492	0.0000*
sd961	0.2750	0.0750	13.4474	0.0002*
sd962	0.4131	0.0527	61.4248	0.0000*
roof921	-0.1367	0.0407	11.2518	0.0008*
roof922	-0.1163	0.0390	8.8990	0.0029*
roof931	-0.1973	0.0380	26.9165	0.0000*
roof932	-0.0960	0.0369	6.7534	0.0094*
roof941	-0.1299	0.0316	16.9153	0.0000*
roof942	-0.0864	0.0360	5.7493	0.0165*
roof951	-0.1011	0.0427	5.6114	0.0178*
roof952	-0.0249	0.0340	0.5355	0.4643
roof961	0.0255	0.0494	0.2655	0.6064
roof962	-0.1432	0.0258	30.7236	0.0000*
nat_for_dist	-0.0072	0.0044	2.6691	0.1023
nat_for_dist942	-0.0060	0.0082	0.5435	0.4610
nat_for_dist951	0.0074	0.0116	0.4057	0.5242
nat_for_dist952	0.0028	0.0085	0.1094	0.7409
nat_for_dist961	0.0178	0.0088	4.1168	0.0425*
nat_for_dist962	0.0094	0.0088	1.1563	0.2822

Table 21 (cont'd): OLS regression results of model excluding vegetation and slope variables. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
fire_dist	-0.0040	0.0011	13.8991	0.0002*
fire_dist942	-0.0001	0.0022	0.0029	0.9567
fire_dist951	0.0056	0.0032	3.0906	0.0787**
fire_dist952	-0.0004	0.0024	0.0279	0.8674
fire_dist961	-0.0065	0.0024	7.5197	0.0061*
fire_dist962	-0.0042	0.0023	3.4410	0.0636**

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720
R^2 = .6134
adjusted R^2 = .6094

All structural variables in the four estimations are of the expected sign and with the exception of *hot_tub* are significant at a minimum of 5% in all four estimations. Both age and primary mobile structures detract from price. There is a significant premium for waterfront property and primary mobile homes are heavily discounted. Across the three neighborhoods, the general price level fell sharply in the first half of 1995. Absent any other shocks to the local housing market, this is evidence of a fire-induced overall decline in the general price level for residential housing in Chelan County. For the variables serving as proxies for overall differences in location and urban development only the log of median household income is significant across all four estimations.

The coefficient estimate for *fire_dist* is negative and highly significant across the four models, indicating that prior to the fires households placed a premium on living near the area that would burn. An additional kilometer from the burned area prior to the fire discounts price by $492 for the 90-meter model, $493 for the 190-meter model, $494 for the 510-meter model, and $461 for the model with no vegetation or slope. The negative coefficient estimate of *fire_dist* reveals that the area that burned, in its unburned state before the second half of 1994, possessed some qualities that were unique from the rest of the national forest. I cannot specifically identify characteristics of the burned area for which households would have a positive willingness to pay for proximity before the fires. However the coefficient on *fire_dist* indicates that the residential housing market capitalized qualities of this area such as viewshed or recreation prior to the 1994 fires. The coefficient on *fire_dist951* is positive and significant for the four models. For the first half of 1995, an additional kilometer from the burned area adds $152 to price for the 90-meter model, $158 for the 190-meter model, $134 for the 510-meter model, and $183 for the model with no vegetation or slope. The coefficient for *nat_for_dist* is significant for only the 510-meter estimation- an additional kilometer from the national forest discounts price by $974 prior to the fires. None of the distance to the national forest interaction variables (*nat_for_dist942*, etc.) are significant. These results seem to reveal that while the fire had no impact on the overall value that households place on living near the national forest, the value for living near the burned area did fall in response to the decreased amenity level.

The signs on the coefficient estimates of the roof and sales date interaction variables indicate that having a fire-resistant roof detracted from the price of a house from the beginning of 1992 through the beginning of 1994. The value of a fire-resistant roof increases sharply in the second half of 1994 (though still negative), stays roughly the same through the first half of 1995, and becomes insignificant for twelve months afterward. This pattern shows a general increase for the willingness to pay for self-protecting with a class A roof beginning in the six month period the fire occurred and is consistent across the three estimations. The change in *roof* from the first half of the sample to the 24-month period beginning in the second half of 1994 is confirmed with a test for the difference in the mean coefficient. The small sample difference in means test statistic for unequal sample variances is

$$(39) \qquad t = \frac{\overline{\beta}_1 - \overline{\beta}_2}{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^{1/2}}$$

where $\overline{\beta}_1, \overline{\beta}_2$ are the mean coefficients, S_1^2, S_2^2 are the sample variances, and n_1, n_2 are the sample sizes. The *t* statistics in Table 22 indicate that the mean coefficient of *roof* is statistically different in the two periods for all four estimations.

Table 22: Difference in mean coefficient of *roof*

	first half 1992 - first half 1994			**second half 1994 - first half 1996**			
	mean coeff	**variance**	**n**	**mean coeff**	**variance**	**n**	***t***
90m	-0.1334	0.0013	5	-0.0461	0.0035	4	-2.5974
190m	-0.1346	0.0013	5	-0.0461	0.0034	4	-2.6454
510m	-0.1359	0.0014	5	-0.0484	0.0036	4	-2.5434
no veg or slope	-0.1352	0.0015	5	-0.0467	0.0034	4	-2.6073

The risk proxies for the amount of vegetation in the household's neighborhood do not exhibit any definitive responses to the fire. In fact, based on these results there is little evidence that there is any value (positive or negative) placed on a larger amount of fuel surrounding a house. As discussed in the policy chapter, this seems to indicate that households place little or no value on the reduction of community risk. Based on the R^2 statistics there is not much difference in the four estimations- the 90-meter neighborhood performed the best, followed by the 190-meter neighborhood, the 510-meter neighborhood, and the model with no vegetation or slope. The smaller the area considered for the vegetation and slope variables, the better the model performed. However, *nat_for_dist* was only significant in the estimation with the widest area considered (510 meters).

Tables 23-25, included in the appendix, feature the vegetation and slope variables interacted with the sales date. The general results for the structural, roofing, and neighborhood risk variables are consistent with those for the primary (simpler) models. In the primary estimations, *nat_for_dist* was significant only when considering a 510-meter neighborhood of vegetation and slope. When the sales date dummies are interacted with these neighborhood risk proxies, *nat_for_dist* is significant for all three neighborhoods. An additional kilometer from the national forest discounts price by $1,041 for the 90-meter model, $1,211 for the 190-meter model, and $1,389 for the 510-meter model. These values do not change as a result of the fire. The coefficients on *fire_dist* are similar to those in the primary estimations. However, the coefficient on *fire_dist951* is significant for only the 510-meter estimation- for the first half of 1995 an additional kilometer from the burned area adds $290 to price. Finally, the 190-meter model performs the best based on the R^2 values, followed by the 90- and 510-meter models. Comparing the results of these more complex models with those of the primary estimations (Tables 18-21) indicate that the performance of the models and the estimates on the distance measures are sensitive to how the neighborhood risk proxies are specified.

The models which produced the results in Tables 18-21 and 23-25 are richly specified, with nine sale date dummies which are interacted with several amenity and risk proxies. A parsimonious model was also estimated and compared to the more complex estimations. This model excluded the half-year sale date dummies and included only a single before fire/after fire sale date dummy. This sale date dummy was interacted only with *fire_dist*. Although the sale date dummy and *fire_dist* were both highly significant, the distance to fire sale date interaction variable was not significant. This illustrates the need to use the richer specification to measure the fire's impacts.

The coefficients on the variables in the full models (Tables 18-21) that could be related to the 1994 fires behave in a similar fashion. All of the effects described above begin in the second half of 1994 or first half of 1995. The value of being located near the burned area declines for the first six months of 1995. The hedonic price for self-protecting with a fire resistant roof shows a general increasing trend beginning in the second half of 1994. Since the fires began in late July 1994 and were suppressed in September, it is strange that stronger effects are not detected in the second half of 1994. This could be due to some information lag, or only because of the time gap between the commitment to buy a house and the closing.

The second common effect is the temporary nature of the coefficient changes. With the exception of the change in the willingness to pay for a fire-resistant roof, these impacts disappear after six to twelve months. It is especially unclear why the amenity effect, the change in the willingness to pay to live near the fire boundary, is so short-lived. Even today, after almost nine years, the forest still bears the scars of the fires. In some areas large amounts of standing, dead timber dominates the landscape. In the next chapter I will introduce evidence that the media overstated the *damage* to the county. This overstatement eventually corrected itself as visitors assessed the true damage and the business community launched public-relations campaigns dismissing the hype.

The change in the coefficients for self-protection introduces an interesting question: what was the mechanism by which these variables changed? The answer is linked to the theoretical model and involves changes in the household's subjective assessments of risk to the surrounding neighborhood and risk to their own property. The next chapter deals with these issues and attempts to define the evolution of household risk perceptions in the context of the 1994 fires. I will suggest that the true risk of damage or property loss to the household is very low and that the erratic behavior of the self-protection coefficients is consistent with either a threshold effect or a general lack of awareness of fire risk.

V. INTERPRETATIONS: THE ROLE OF MARKETS AND INFORMATION

The focus of wildfire suppression in recent years has been the protection of human lives and property. This is in sharp contrast to firefighting policy earlier in the century, where fires were suppressed regardless of the human values at risk. As Cortner et al. (1990) explain, individual choices regarding location affect not only the decision makers themselves but also all levels of government and society at large. The federal government assumes the majority of the burden for wildfire suppression. The explosion of large, intense fires in the past decade has brought attention and criticism to the ballooning costs of fighting fires. Local and state agencies also feel the strain during the fire season, when their relatively limited resources are allocated to fighting fires both within and outside of their usual jurisdictions. In light of this shift, the question of how to mitigate risk to property owners introduces some important policy questions. Where should educational programs be directed, at homeowners or local governments? If educational programs are available to interface property owners, will they voluntarily adopt risk-averting measures or accept publicly funded programs to reduce the collective risk level in their communities? Absent voluntary self-protection, will communities pass ordinances and codes that require certain actions on the part of homeowners in the interface?

In this chapter I will interpret my results in terms of the policy options for mitigating risk in the wildland-urban interface. First, based on my theoretical assumptions and the coefficients for self-protection and neighborhood risk from the primary estimations (Tables 18-21), I will examine the level of support for private and collective protection. Next, I will introduce several general models that explain how households respond to a heightened level of information about risk to their property. From this group of models, the coefficient for self-protection will assist in selecting candidates which best describe the data and estimation results. These interpretations will provide guidance about where educational and community assistance programs should be directed and whether it is realistic to expect voluntary acceptance of risk mitigation measures by households. For fiscal years 2001-2003, the National Fire Plan has allocated five million dollars to FIREWISE for community assistance and education. The chapter will conclude with a brief discussion of how extending this research with survey techniques could further refine the interpretations of the data and estimation results.

PUBLIC VS. COLLECTIVE RESPONSES TO WILDFIRE RISK

The household chooses two types of averting activities in its location decision. The first is self-protection, which includes fire-resistant building materials and landscaping in the area immediately surrounding a house. Absent zoning laws, insurance requirements, and construction codes, the decision to self-protect is the household's alone. The level of collective protection is the second type of averting activity in the presence of wildfire risk. Collective measures seek to reduce risk outside of the immediate area around a house. Collective risk is embodied by the characteristics of the vegetation and landscape in the household's neighborhood and is shared by others. Hence any attempt to reduce this risk level cannot be undertaken by a single household. The effort must be community-wide, or undertaken by public entities on the part of households. The willingness to pay for the two types of protection from wildfire risk can be inferred by examining the coefficient estimates on *roof* and the various vegetation and slope variables.

The marginal willingness to pay for private or self-protection from wildfire risk is simply the hedonic price of a class A fire-resistant roof,

$$\text{(40)} \quad \text{MWTP for self-protection} = \frac{\partial\, lnP}{\partial\, roof}.$$

The empirical application does not include a variable representing collective protection. However the marginal willingness to pay for these activities can be inferred from the results. Recall that the level of collective averting behavior (G) is a determinant of collective or community wildfire risk (α^C). Collective risk increases in forest condition (or vegetation density from the empirical model) and decreases in collective protection. Since the neighborhood measures of vegetation and slope are proxies for the risk component of forest condition, their coefficients can reveal something about the marginal willingness to pay for collective protection. From equation (4) collective risk is non-increasing in the level of collective protection, so the household's marginal willingness to pay is proportional to the negative of the coefficients on the neighborhood risk proxies,

$$\text{(41)} \quad \text{MWTP for collective risk reduction} \approx -\frac{\partial\, lnP}{\partial\, risk}$$

where *risk* represents *egreen*, *shrub*, *grass*, *slope*, and *veg_slope* for the three neighborhood sizes.

Based on the signs of the coefficients for *roof* and the neighborhood risk proxies, I can infer whether the household supports self-protection, collective protection, both, or neither. Consider a matrix for summarizing the possible responses to wildfire risk. The coefficient signs are those that would signify support or lack of support for the various responses.

Type of Protection Supported by Household	Sign of Hedonic Price of Fire-Resistant Roof	Sign of Hedonic Price of Neighborhood Risk
Self-Protection & Collective Protection	+	-
Self-Protection but not Collective Protection	+	+/0
Collective Protection but not Self-Protection	-/0	-
Neither Self-Protection nor Collective Protection	-/0	+/0

Figure 12: Matrix relating the signs of coefficients for risk proxies to support for self-protection and collective protection from wildfire risk.

For example, the second row in Figure 12 indicates that if the household supports self-protection but not collective protection, then the sign on *roof* would be positive while the signs of the neighborhood risk proxies would be either positive or zero.

Relating the results obtained in the estimation of the full model (Tables 18-21) to Figure 12, households were not willing to pay for collective risk reduction before or after the fires. Prior to the fires households were also not willing to pay for private self-protection. For the five six-month periods prior to the fires, the hedonic price of a Class A fire resistant roof is negative and highly significant for all three neighborhood estimations. However, the post-fire hedonic prices for roofing type indicate a temporary increase in the marginal willingness to pay for self-protection. The hedonic price of a fire resistant roof increases in the last six months of 1994 and stays roughly the same in the first half of 1995. The hedonic price is insignificant for the twelve-month period of mid 1995 to mid 1996. The difference in means for the coefficient estimates of *roof* (Table 22) substantiates this shift. It should be noted that although the willingness to pay for a fire resistant roof increases substantially after the fires, it never turns positive and significant. A possible explanation is correlation between the fire-resistant qualities of the roof and its appearance. Recall that the theoretical model separated out the averting (A) and appearance characteristics (Z_A) of self-protection activities. I am unable to do that here, so the coefficient on roofing type likely embodies both the fire-resistant and aesthetic components of the roof. However, if the household's valuation of the aesthetic quality of the roof is constant over the sample time frame, then any change in the hedonic price is due to a change in the value placed on the protection qualities. As noted in the analysis of the empirical results, the neighborhood risk measures do not exhibit any response to the fires.

Support for these results from previous work is mixed. In a survey of homeowners in rural Michigan, Winter and Friend (2000) found that while participants believe it is their responsibility to fireproof their own property, the lower aesthetic characteristics of brush-clearing and fire-resistant building materials are not worth the increased protection they afford. While opinions regarding investment in public infrastructure such as roads and improved fire suppression equipment were not negative, neither was there a positive theme beyond the need for government to respond to fires. Prescribed burning was generally not supported because of the risk of escape. The view that collective protection measures may not be effective in reducing risk or may actually increase risk could drive households to adopt self-protective measures. Other work finds moderate to strong support among homeowners and recreational users of forestland for these and other government risk-reduction activities (Cortner et al. 1984, Manfredo et al. 1990, Gardner et al. 1985).

Other explanations are possible for the lack of significance of the neighborhood risk measures. The "lightning doesn't strike twice" rationalization is one possibility. Residents may feel that risk has actually decreased because of the event. This may be true in the very short run, but is not accurate. First, the entire county did not burn. The fires did not affect large areas of the Wenatchee National Forest. Further, even within the fire boundaries everything did not burn. The fires burned mosaic patterns and left areas of unburned vegetation within the boundaries. The unburned portions within the fire boundaries as well as opportunistic species such as grasses that grew in burned areas after the fire kept the risk of fire from decreasing substantially. Another explanation for the lack of significance on the neighborhood risk proxies is that the expectation of government suppression of wildfires may create a moral hazard. Why a support collective protection to mitigate risk when it is certain the government will expend resources to extinguish a fire that is threatening a community? Finally, vegetation and slope are only two variables among many that determine the risk of wildfire in a community. The broad nature of the risk proxies I have chosen leaves opportunities for future work to refine how households value public-sector contributions to risk reduction.

Information can also play a powerful role in how households perceive the risk from wildfire and therefore value risk reduction measures. In the section that follows, I will further develop the theoretical model to take into account the role of information in the behavior of the hedonic prices.

THE ROLE OF INFORMATION IN RISK PERCEPTIONS

A brief review of the literature on the relationship between subjective risk, objective risk, and information will assist in tying together the theoretical model and the transient results obtained in the estimation. First, define objective risk (α^o) as the household's true risk of property damage from wildfire (in contrast to the household's *subjective or perceived* risk, α^S). It has been previously established that individuals understate risk for events where the objective risk is high or above average and overstate risk for events where the objective risk is low or below average. This is represented in Figure 13.

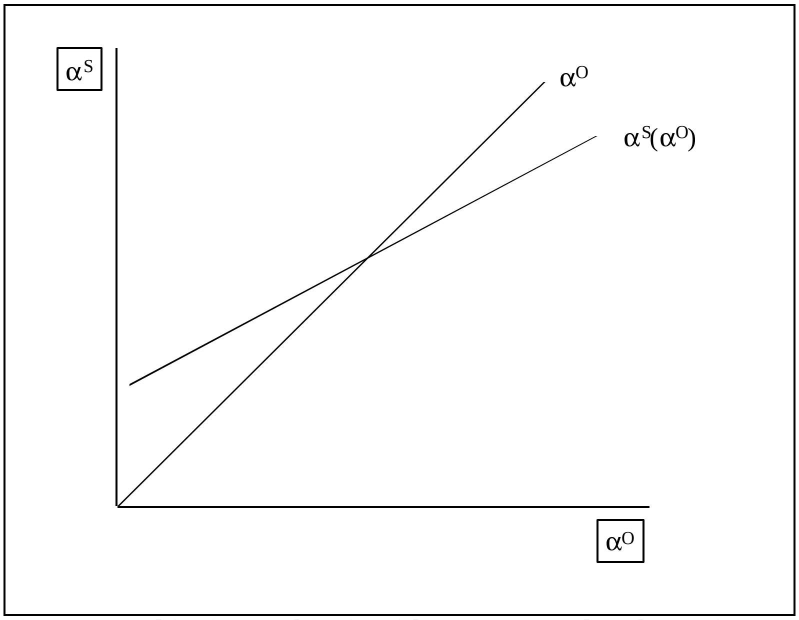

Figure 13: Subjective vs. objective risk. Source: Kask and Maani (1992).

Kask and Maani (1992) define these findings as transformation bias, which can exist regardless of the information level. They also suggest a second source of potential bias. The impact of poor information, information bias, can exaggerate the existing differences between subjective and objective risk levels due to transformation bias. Further, Viscusi and Magat (1987) find that additional information increases perceived risk when the true risk is high and decreases perceived risk when it is initially high. Figures 14 and 15 draw on the Kask and Maani (1992) synthesis of the two sources of bias and the Viscusi and Magat (1987) results of the evolution of perceived risk in response to an increase in information.

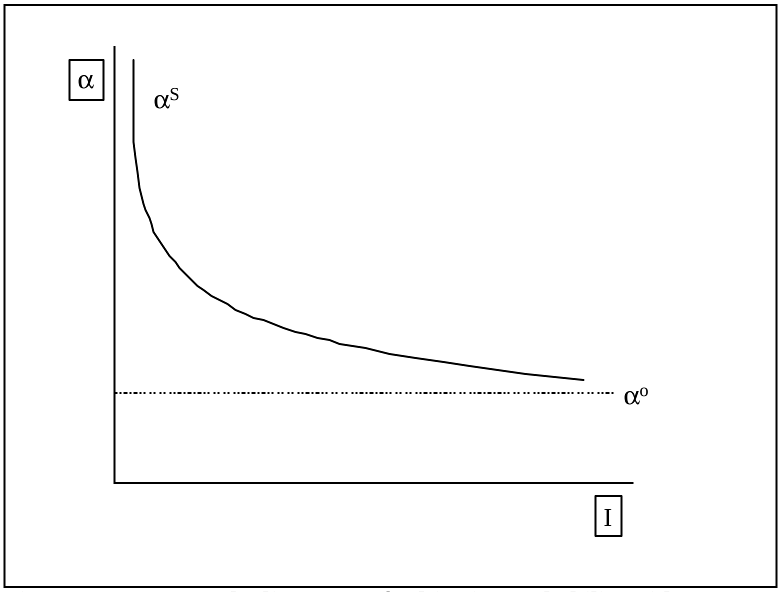

Figure 14: Downward adjustment of subjective probability with increased information where the objective risk level is low. Source: Kask and Maani (1992).

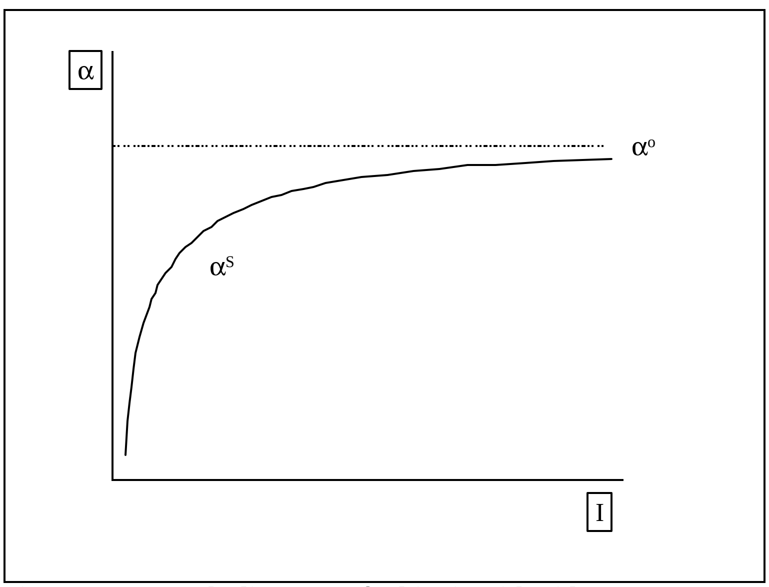

Figure 15: Upward adjustment of subjective risk with increased information where the objective risk level is high. Source: Kask and Maani (1992).

Threshold behavior is another manifestation of transformation bias. Kunreuther et al. (1978) suggest that subjective risk is translated to a level at or near zero if individuals believe the true risk to be less than the threshold, α^T. To illustrate how a threshold impacts household decision-making, consider Figure 16. To the left of point E the true risk level is low and subjective risk is overstated. However the presence of a threshold with low true probabilities will translate the subjective risk levels to zero if they are less than the threshold. The nature of this translation depends on the prevailing information regime. Under high information, the household is better able to ascertain the true objective risk level and can compare it to the threshold level of risk. To the left of point T, the true level of risk is less than the threshold, so the corresponding area of the subjective risk line (to the left of B) will be at or near zero. With a low information regime, the household is less able to approximate the true level of risk and the subjective risk level must be compared to the threshold. With low information, the effective perceived risk to the left of A is at or near zero.

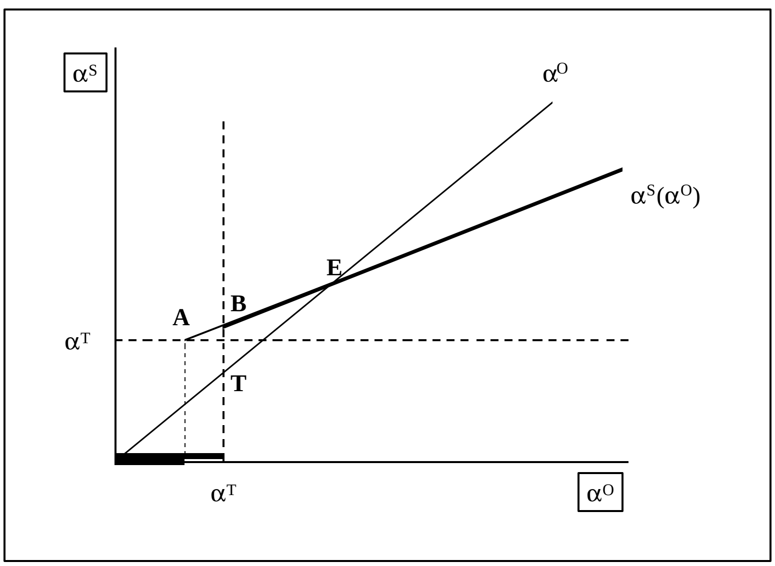

Figure 16: The effect of a threshold under high and low information.

Figure 19 repeats Kask and Maani's (1992) representation of threshold behavior where the objective risk is low and below the threshold level ($\alpha^o < \alpha^T$), which is represented by the portion of the true risk line to the left of point T in Figure 16. At zero or low levels of information the household is unable to determine the true level of risk, so the effective subjective risk level is at or near zero (corresponding to the area along the horizontal axis to the left of point A in Figure 16). As information increases, the subjective risk level increases. At some critical level of information (I^C) the household is able to better assess the objective risk level. Initially the household realizes it has overestimated the objective risk and adjusts subjective risk down. Once the household realizes that the objective risk is less than the threshold (corresponding to part of the true risk line to the left of T in Figure 16), the subjective risk quickly falls to zero (the area along the horizontal axis to the left of B in Figure 16). To the left of I^C, the subjective probability begins near zero because the household does not know the objective probability but is aware that the true subjective probability is less than the threshold. To the right of I^C, the subjective probability goes to zero because the household, due to the higher level of information, is better able to approximate the objective risk level and realizes that it is less than the threshold. The "don't know" versus "don't care" distinction for underestimating low objective probabilities in the presence of threshold behavior is an important point.

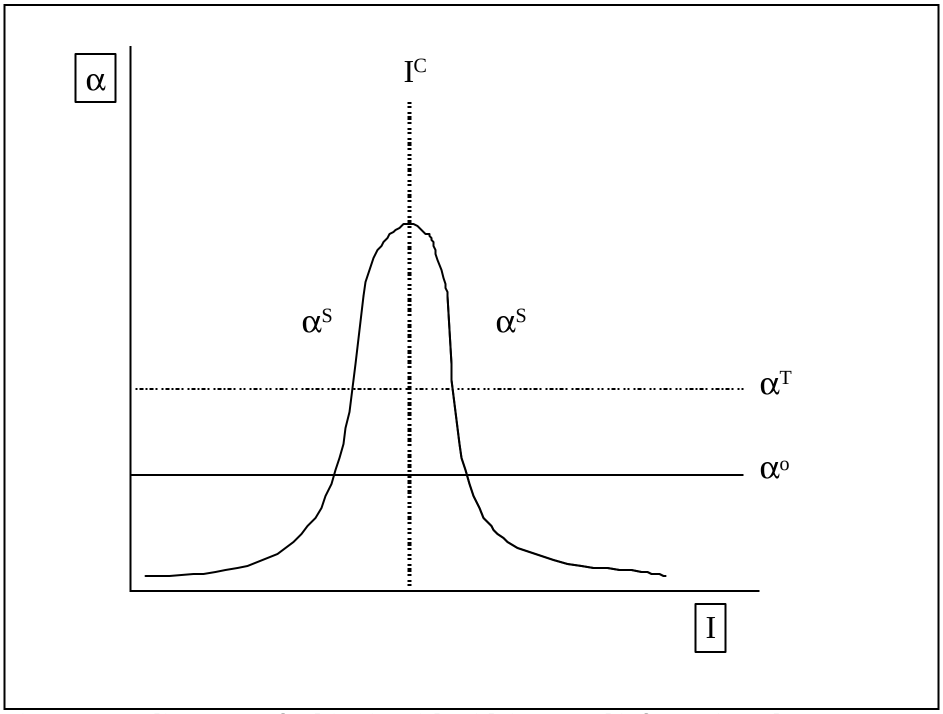

Figure 17: Adjustment of subjective risk with increased information where objective risk is less than the threshold. Source: Kask and Maani (1992).

Subjective risk could be understated with low information and a low true risk even in the absence of a threshold. Consider Figure 18. With the level of information initially low, the risk of fire is not on the household's "radar screen." There may be no reason to think about fire risk or the household may have other things to consider, so the effective subjective risk is near zero. As information increases, the household becomes more aware of the true risk and may even overstate it, but with sufficient information the subjective risk level will approach the true level. This explanation is closely related to the concept of a threshold, but is different because the household is not actively thinking about risk, whereas with a threshold there are deliberate comparisons between the threshold and the subjective and true risk levels. Also, with high enough information the subjective risk approaches the true level. However in the presence of a threshold high information still leads to a zero subjective risk.

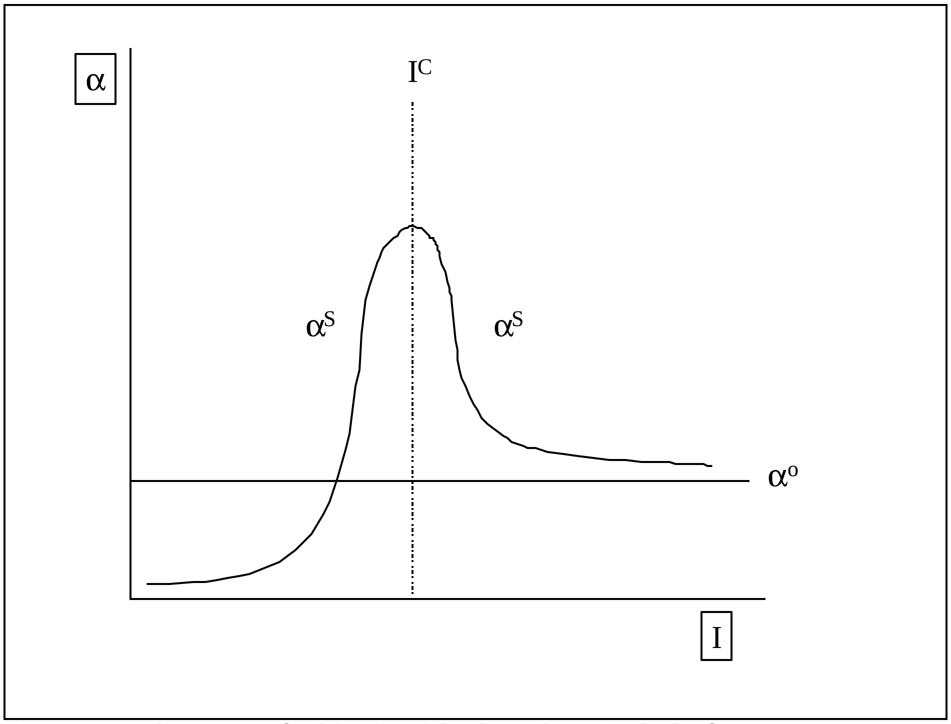

Figure 18: Adjustment of subjective risk where there is a lack of awareness

INTERPRETATIONS

The 1994 fires in Chelan County are a natural experiment for determining how household risk perceptions of wildfire risk respond to the introduction of information. Observing the behavior of the coefficient estimates for self-protection and relating these to the two sources of bias will provide insight into both the initial relationship between perceived and objective property damage risk and the reaction of perceived risk to new information. Beron et al. (1997) present four possibilities describing how hedonic prices respond to changes in subjective probabilities as a result of increasing levels of information. Presenting these in terms of my model will assist in synthesizing the estimation results, the sources of bias, and the response to new information.

Case 1: If the initial household estimate of the probability of damage exceeds the true probability ($\alpha^S > \alpha^O$) then a decrease in the hedonic price of self-protection is consistent with a downward revision in the subjective probability.

Case 2: If the initial household estimate of the probability of damage exceeds the true probability ($\alpha^S > \alpha^O$) then an increase in the hedonic price of self-protection is consistent with an upward revision in the subjective probability.

Case 3: If the initial household estimate of the probability of damage is less than the true probability ($\alpha^S < \alpha^O$) then an increase in the hedonic price of self-protection is consistent with an upward revision in the subjective probability.

Case 4: If the initial household estimate of the probability of damage is less than the true probability ($\alpha^S < \alpha^O$) then a decrease in the hedonic price of self-protection is consistent with a downward revision in the subjective probability.

To determine which of the four Cases are candidates for explaining my results, I will begin by showing that the hedonic price of self-protection and perceived risk move in the same direction in response to new information. Consider first a decrease in the perceived risk of property damage. To see why the hedonic price of self-protection must decrease as a consequence, consider again the relationship from equation (29)

$$\text{(42)} \qquad \frac{dP_H}{dA} = \frac{\alpha_A^S\left(v^S - v\right)}{\alpha^S v_X^S + \alpha^C v_X^C + \left(1 - \alpha^S - \alpha^C\right)v_X}.$$

The right hand side is the marginal benefit of self-protection: the monetized reduction in expected damages from an incremental unit of self-protection. From (18), the left hand side of (42) is

(43) $$\frac{dP_H}{dA} = \frac{\partial P_H}{\partial A} + \frac{\partial P_H}{\partial \alpha^S}\alpha_A^S.$$

If the perceived risk of property damage declines, expected damages declines. Because (42) must hold, the household's willingness to pay for self-protection, $\frac{dP_H}{dA}$, must fall as well. This makes intuitive sense because with an overstated initial subjective risk level, increased information will dampen (make less negative) the marginal impact of an additional unit of self-protection on subjective risk (α_A^S) as the subjective risk level falls toward the true level. As the household is better able to approximate the low true risk level, an additional unit of self-protection is less likely to affect the subjective risk assessment. So observing a decreasing hedonic price for self-protection is consistent with perceived risk that is initially too high and is adjusted downward toward the true risk level as information increases.

An increase in the subjective risk of property damage is accompanied by an increase in the hedonic price of self-protection. Here subjective risk is increasing in response to new information so expected damages increase. From (42) and (43) the marginal willingness to pay for self-protection must increase as well. The marginal product of self-protection (α_A^S) will increase (become more negative) as the increase in information induces an upward revision of subjective risk toward the true level. As the household is better able to approximate the high true risk level, an additional unit of self-protection is more likely to affect the subjective assessment. Observing an increasing hedonic price for self-protection indicates an initial level of subjective risk that is too low and is revised upward toward the true risk level with increased information. These changes in the hedonic price of self-protection are manifestations of a shift in the hedonic price function induced by the fires.

Cases 1 and 4 can immediately be ruled out as descriptions of my estimation results, since in both the hedonic price is decreasing in response to new information. This leaves Cases 2 and 3. Figures 17 and 18 are also candidates, as they embody both an increase and a decrease in subjective risk and the hedonic price of self-protection. To the left of I^C, subjective risk and the hedonic price for self-protection rise in response to more information after an initial underestimate of the low objective risk level. The opposite occurs to the right of I^C.

Case 3, corresponding to Figure 15, alone is a candidate for explaining the estimation results. The increasing hedonic price of a Class A fire-resistant roof, $\frac{\partial lnP}{\partial roof}$, from the second half of 1994 through the first half of 1996 is evidence of an initially low subjective risk level that was revised upward in response to the information on wildfire risk that accompanied the fires. As I'll explain below, I assume that the 1994 fires in Chelan County were events that increased the level of information about the prevailing level of wildfire risk either through being near the fire itself, newscasts or radio broadcasts of news about the fire, or public information campaigns that followed the fire. Information may have decreased at some point, inducing a decrease in the hedonic price in the last half of 1996 (see Figures 20 & 21). If Case 3 and Figure 15 represent the evolution of perceived risk, then from the previously established understanding of risk perceptions (that households underestimate events with above average risk) it must be that the true risk to the household of property damage is relatively high or above average. This is not consistent with what we observe in general or in the case of the 1994 fires in Chelan County. For example, even though the overall risk of fire in Chelan County is relatively high, the actual risk to the household of property damage is quite low. Despite the large area burned by the 1994 fires, the property damage was relatively light with 37 homes and 76 outbuildings destroyed (Carroll et al. 2000). I therefore rule out Case 3 as an explanation for the behavior of the hedonic prices of self-protection.

Based on the result that the hedonic price for self-protection moves in the same direction as the perceived risk level, Case 2 is also a candidate for explaining the estimation results. As Figure 19 illustrates, even if the household had been close in its initial approximation of the true risk level, over-hyping of the true risk level could result in an increase in the subjective risk level and hedonic price for self-protection.

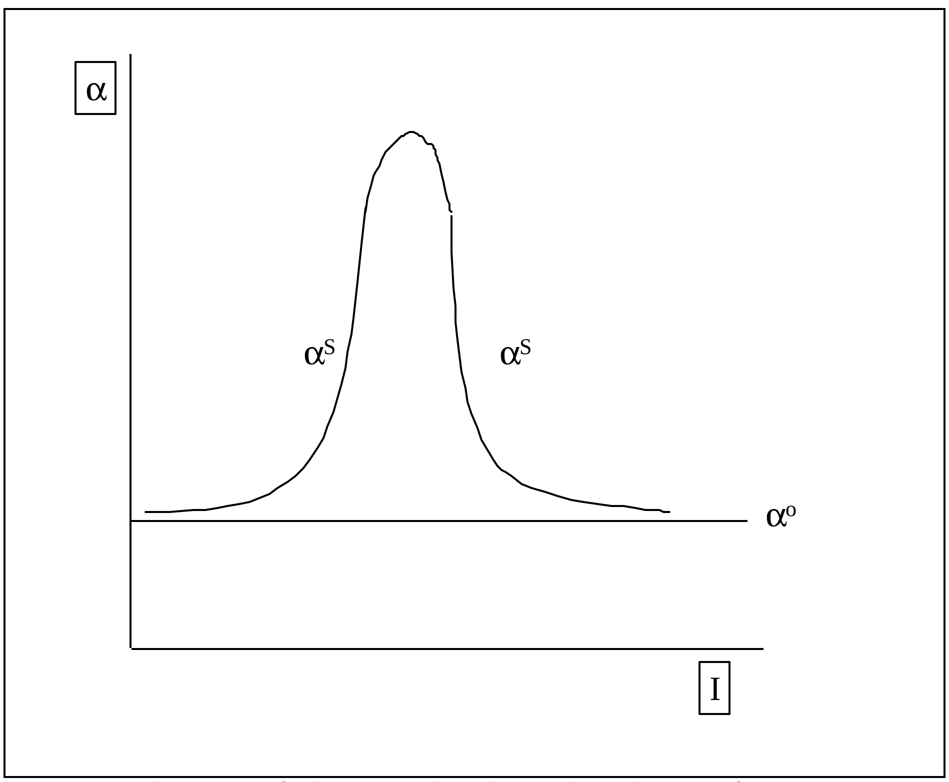

Figure 19: Adjustment of subjective risk with initial over-hyping of true risk.

I rule out Case 2 because it implies an over-hyping of the risk to households during and following the fires. My survey of the sources of information during and after the fire found no evidence of over- or under-hyping by the media that would lead to more inaccurate assessments of wildfire risk (although I will argue that there was over-hyping of damage to the forest).

Figures 17 and 18 represent more plausible explanations. Given a very small objective risk of property damage, even if the household's true subjective risk substantially overestimated that true risk at low information levels, a zero effective subjective risk could result if either the threshold value is high enough (Figure 17) or if fire was not even thought about (Figure 18), leading to very low hedonic prices for a fire-resistant roof for the first half of the sample. As information increased during and after the fire, the subjective assessment of property damage also increased leading to an increase in the hedonic price for the roof variable from the second half of 1994 through the first half of 1996. The decrease in the hedonic price of a fire-resistant roof in the second half of 1996 to pre-fire levels could be due either to crossing the critical information threshold (I^C) where the household realizes the true risk is below the risk threshold in Figure 17, or a decrease in information after the initial increase in either Figure 17 or 18 (so the household moves back down the subjective risk curve to the left of I^C in Figures 17 and 18). For the latter scenario where the change in information is non-monotonic, if the information level behaved in a manner consistent with Figure 20, initially increasing then decreasing after a certain point, then the subjective risk level would exhibit similar behavior as shown in Figure 21.

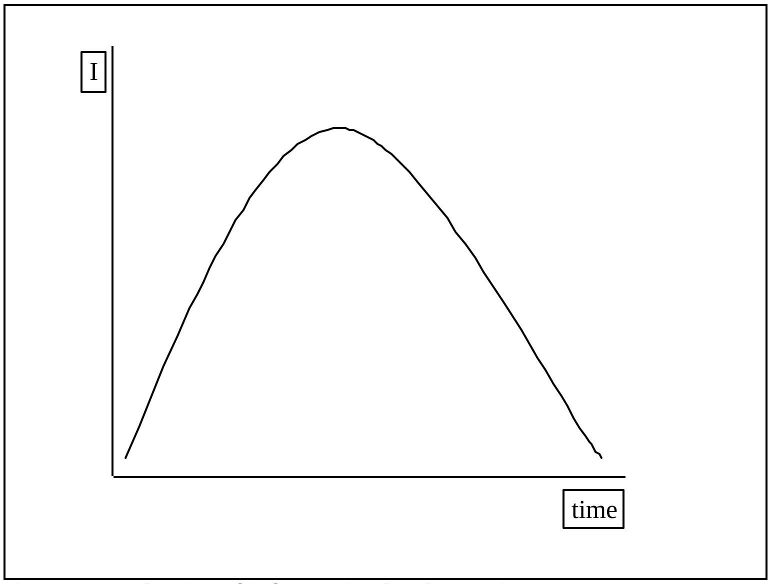

Figure 20: Behavior of information level over time

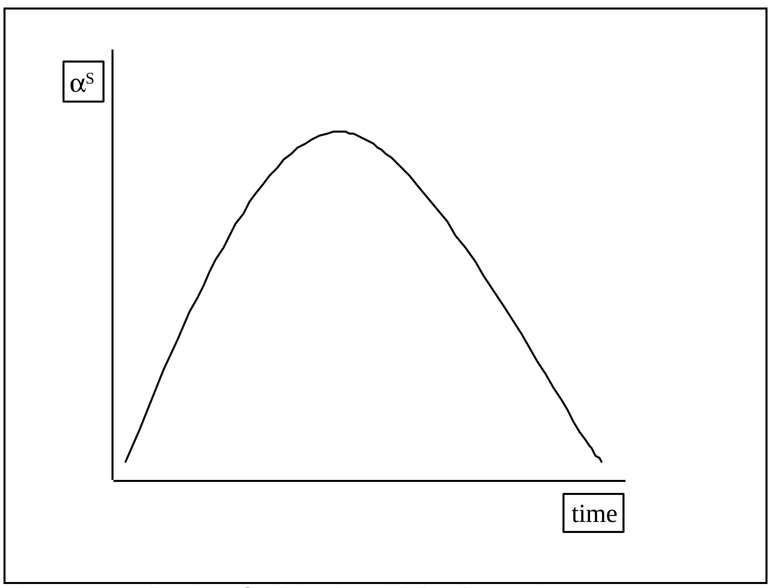

Figure 21: Behavior of subjective risk level over time

The profiles of information and subjective risk in Figures 20 and 21 correspond to the portion of Figures 17 and 18 to the left of I^C. As information increases the household moves up the subjective risk curve. After information reaches a maximum and decreases, the household slides back down the subjective risk curve, ending up at or near where it started- with a very low subjective risk level and hedonic price for self-protection.

From my analysis of information sources, it is difficult to ascertain the profile of information after the fire- a monotonic increase or initial increase then a decrease. As I will show, through at least the summer of 1995 efforts were made to provide education to homeowners on risk mitigation measures. My review of media sources shows that Chelan residents did not take advantage of these opportunities to learn about methods of self-protection.

In the final policy analysis, I will argue that the reason the hedonic price of self-protection reversed in late 1996 is not important if a risk threshold exists, as in Figure 17. Whether information increased monotonically or increased then decreased after the fire would be irrelevant. Given the very small risk to the household of property damage or destruction and a risk threshold that yields very low subjective probabilities even with a high level of information, the household would end up at the same place- a low willingness to pay for self-protection. The presence of the threshold results in low hedonic prices for self-protection under regimes characterized by very low or very high information. Absent mechanisms to induce a downward adjustment in the threshold level of risk, there may be little that can be done to obtain voluntary acceptance of private and collective risk reduction strategies (evidenced by an increase in the willingness to pay). Even if educational programs induced a downward adjustment in thresholds, households would not necessarily adopt self-protecting measures. The increased level of information that accompanies educational campaigns would enable the household to equate subjective risk to the very low objective level, which would correspond to low willingness to pay values for self-protection. However if household risk perceptions evolve according to Figure 18 then the reversion of the hedonic price in late 1996 to pre-fire levels must be due to a decrease in information. With this scenario there is an opportunity for educational programs to increase awareness of fire risk. The challenge would be in maintaining a "volume" sufficient for the household to correctly assess the true level of risk.

A TEMPORAL AND SPATIAL PROFILE OF INFORMATION

An examination of the media coverage during and after the 1994 fires in Chelan County will provide insight on the evolution of information. In this section I will evaluate the media on its performance in communicating both the extent of wildfire-inflicted damage to the forest resource and the risk to property owners. I will show that although the media overstated the extent of damage, an accurate portrayal of risk to property owners was provided. Throughout the fire, The Wenatchee World (*TWW*) carried news about the fire and is a valuable source for exploring how information about fire risk was communicated both during and after the fires. News outlets in the Seattle and Portland areas will be useful in examining how the fires were perceived on the west side of the Cascades.

On Sunday July 24, 1994 *TWW* forecasted a "slight chance of a shower or thunderstorm" for the Wenatchee Valley. The following day the paper reported that a thunderstorm the previous evening had ignited around 41 fires in the Wenatchee National Forest. On Thursday July 28 *TWW* began a "Fire facts" summary on the front page that outlined the number of casualties, evacuations, road closings, number of buildings lost, and acreage burned in Chelan County. By 11 A.M. that morning the largest fire, the Tyee, had grown to 54,000 acres. During the height of the fires, town meetings held by local public officials and federal fire officials in Chelan, Entiat, Leavenworth, and Wenatchee provided a forum to discuss issues and answer questions (*TWW* 07/29/94, 08/01/94, 08/19/94). A local radio station in Chelan provided constant information and updates on fire conditions, road closings, and relief effort coordination (*TWW* 08/02/94). A theme often repeated in *TWW* during the 1994 fires is the overall high level of fire risk and history of large fires in Chelan County (*TWW* 07/27/94, 08/03/94, 08/06/94, and 08/07/94).

This profile indicates that there was no under-hyping of the risk of property damage or destruction during the fires. I similarly reject the notion of over-hyping of risk. Even though worst-case scenarios did not become reality, *The Seattle Post-Intelligencer* (*TSPI*) relates the opinions of fire officials that dry and windy conditions held the potential for a disaster (10/26/94). Even the city of Wenatchee, the largest population center in the Chelan County, was under the threat from the Hatchery fire, and plans were laid to evacuate the western portion of the city if the fire crossed Mission Creek (*TWW* 07/31/94, 08/03/94). According to *The Seattle Times* (*TST*) the threat to Wenatchee was real enough that a firebreak twenty feet wide and fifteen miles long was built west of the city as a last defense (07/02/95). I confirmed the presence of the firebreak in a conversation with the Chelan County Fire Marshal.

Even though the media coverage of the fires themselves tapered off in mid-September other sources of information on interface fire risk prevailed. I did not find evidence that their messages were being heard. In the aftermath of the fires information campaigns to increase awareness of fire risk among homeowners were given little attention. Educational events in late September 1994 in Chelan and neighboring Okanogan Counties were poorly attended (*TWW* 10/03/94). This trend continued into the summer of 1995 when a seminar on making homes more fire-resistant drew no attendees (*TSPI* 07/24/95). Fire officials feared that people had lost interest, a common occurrence in the months following a fire, but at the same time acknowledged that fire-resistant building materials are no guarantee against damage (*TST* 07/02/95). Fires burning in the Wenatchee National Forest during the summers of 1995 and 1996 (*The Columbian* 09/05/95, 09/01/96; *TSPI* 09/06/95) provided a reminder to residents that fire risk had not diminished in the wake of the previous summer's devastation. Even the county administration turned a deaf ear to suggestions for decreasing risk to property including requiring fire-resistant roofs, improved access for fire vehicles, and defensible space around structures despite the urgings of local fire officials (*TSPI* 07/24/95, 07/27/95). Previous opposition from industry groups to local and state efforts to reduce property risk and a desire not to bend to the wishes of the environmental community were given as reasons for the lack of a county policy at the time of the fires (*TWW* 08/09/94). In the summer of 1996 the governor of Washington ordered Chelan's share of the gas tax withheld for failing to comply with the state's 1990 Growth Management Act, which was designed to stem urban sprawl in rapidly growing counties (*TSPI* 07/02/96, 10/18/96).

There is evidence the perceived level of fire *damage* was overstated. The business community in Chelan County was a very vocal critic of media hype. Tourism fell off sharply during the fires (*TWW* 07/31/94, *TST* 10/02/94), and some in the business community and members of local government thought that the media had overstated the damage to the forest and tourist attractions (*TWW* 07/31/94 and 08/08/94, *TST* 08/11/94 and 08/21/94, *TSPI*

09/06/94). Major news network reported that Chelan, a town of a little over 3,200 at the time of the fires, had evacuated 300,000 residents and that Lake Chelan would be choked with pollution from the fires for years (*TWW* 07/31/94, *TST* 08/11/94). Some visitors to county after the fires found that the damage was not as bad as they had expected given the media coverage (*TWW* 08/08/94, *The Columbian* 08/14/94, *TSPI* 09/06/94, *TST* 10/02/94). The fires did not burn everything inside the boundaries illustrated in the previous chapter. My own observation confirms that the fire burned a mosaic pattern, leaving unburned sections. Looking at a map such as in Figure 5 would give the impression that the entire area within the boundaries was destroyed. To combat the perception that flames had consumed the entire county, local business groups and governments launched public-relations campaigns, with special attention given to the Seattle and Puget Sound areas (*TWW* 08/05/94, 08/08/94, 08/10/94, 08/15/94). The over-hyping of fire damage, followed by the realizations of visitors that damages were not as bad as expected, and the efforts by the local community to bring tourists back, helps to explain the transient nature of the coefficient of *fire_dist*- a decrease in the willingness to pay to live near the burned area only in the first half of 1995.

POLICY IMPLICATIONS

The suppression of wildfires is directed at protecting human lives and property. The wildland-urban interface is expanding, especially in the interior west. Households that choose to locate near areas of high fire risk impose a potential social cost outside of the cost of their housing decision. This social cost is comprised of the expenditures necessary to protect property in the event of a fire. Educational programs for reducing risk directed at property owners and local governments “pass” a social cost-benefit test if the cost of the programs plus the cost of mitigation measures to homeowners and governments (from adopting program suggestions) is less than the decrease in suppression expenditures, property damages. There are non-market benefits to risk reduction as well that could affect the benefits. For example, in a contingent valuation study of fire risk reduction measures in California that would protect spotted owl habitat, Loomis et al. (1997) find that the benefits to California residents of the proposed programs were 10 times the estimated costs. I do not intend to conjecture on the effectiveness of self-protection or collective-protection measures in reducing suppression expenditures. However, if obtaining adoption of risk-mitigating behaviors is a social goal then the results from the estimation and the conclusions I have drawn on the nature and evolution of risk and the role of information can provide policy makers some direction for efforts to increase adoption of self-protection.

The true risk to any one household of suffering property damage from a wildfire is very small. I have previously concluded that the evolution of subjective risk and the hedonic price of self-protection can result from the behavior illustrated in either Figure 17 or 18. An increase in information that provided an accurate (not over- or under-hyped) portrayal of interface risk is responsible for the initial upward adjustment of the coefficient for self-protection under both possibilities. Despite an initial increase in the willingness to pay for a fire-resistant roof, the coefficient estimate decreased sharply in the second half of 1996. Whether this decline was due to a decrease in the information level or the crossing of the critical information level where the household observes the true risk level in the presence of a threshold is unclear. However both would produce a low subjective risk level and hence a low willingness to pay for self-protection. The critical policy result is that efforts directed at households to voluntarily undertake risk mitigation measures appear to be misdirected if households possess a threshold level of risk (Figure 17), while a simple lack of awareness due to low information does suggest an opportunity for education programs (Figure 18) designed for household consumption.

Providing information with sufficient volume to keep risk in the minds of households can cure a lack of awareness or help to bring attention to fire risk. With a threshold, however, increasing information to property owners on wildfire risk and mitigation practices will produce the same result as no information at all. With higher information, the household realizes that its true risk is very low (less than its threshold value) resulting in low perceived risk levels and low hedonic prices for self-protection. The estimation results indicate that a middle level of information can induce an increase in the willingness to pay for self-protection, but this may require a delicate balancing act in the design of education campaigns.

With a threshold regime, information and education programs directed at local policy makers may have a better of success. Chelan County has mixed results formulating official polices on mitigating risk to property. The Chelan Fire Marshal indicated that one reason given by Chelan officials for not requiring fire-resistant roofs on all new construction is that many of the structures that burned in the 1994 fires, where dry and windy conditions prevailed, had metal roofs. This may be the case but it ignores the possibility that at least some structures were saved because of fire-resistant roofing. The fire marshal has implemented a fire protection credit program, where houses in new subdivisions receive a credit for having a class A roof to count against any deficiencies in water access. Further, all new development in moderate or higher risk areas must have a class A roof. This program exists for new development on subdivided parcels only, and does not apply to pre-existing lots. This is the only risk mitigation program in the county, as he stated that there were no community strategies that he was aware of.

EXTENSIONS

The estimation results do not allow me to distinguish between the alternative models describing the behavior of subjective risk in response to new information. I have speculated, based on anecdotal evidence, that two of the models describe the results better than the rest. I will briefly suggest some extensions to this research that would provide some further guidance on this issue.

Survey instruments are a popular method for determining attitudes and perceptions regarding risk. The addresses of respondents would provide the location information necessary to determine the true risk to each household in the survey (based on a risk map). The subjective or perceived level of risk would be inferred from the survey responses. The responses would then be compared to the true risk, both before and after the introduction of information. The questions could be relatively simple, such as asking respondents to rate the risk of fire in their neighborhood and the risk of fire damage to their property. The trajectory of subjective risk compared to the true level would assist in determining which models are candidates. Other types of questions could also be useful. For example, Abt et al. ask respondents to rate a group of perceived problems to the community, including crime, drugs, economic problems, tornado damage, and wildfire damage. The mean score for wildfire would indicate the degree to which wildfire is in the minds of respondents.

The ideal situation would be to perform a survey in an area substantially similar to Chelan County prior to a fire to generate a baseline risk measurement, wait for the fire to occur, then survey again to obtain the post-fire perceptions of risk. Unfortunately, wildfires do not announce when they will occur. Two options are available. The first involves surveying an area that has been fire free for a substantial period of time to generate the pre-fire sample. A separate location could be surveyed following a fire to produce the post-fire sample. If information on demographics and income were collected along risk perceptions, a method such as propensity score matching could be used to determine how views on risk are different between the two locations. The realization of a fire is not necessary for the second option. A single location could be sampled. Respondents would answer initial questions regarding their risk perceptions. Following the review of some information regarding risk in their area, they would provide a second assessment of risk. Viscusi and Magat (1987) use a similar technique in determining how the risk perceptions of workers change after they were provided with warning labels for hazardous substances.

The evolution of subjective risk is not the only area where surveys could provide deeper insight into my results. Based on the coefficient estimates on *roof* and the neighborhood risk proxies, I claim that there is an increased willingness to pay for private self-protection and no change in the willingness to pay for collective protection. Abt et al. (1991) and Cortner et al. (1990) perform surveys that ask respondents how they would rate different policy options such as prescribed burning, building material restrictions, mandatory insurance, and zoning plans that restrict construction in hazardous areas. The proper instrument for my work would ask respondents to rate these types of policies, in addition to various voluntary self-protection measures. Mean ratings before and after the provision of information on risk would assist in determining how views on private and collective protection evolve.

VI. CONCLUSION

The physical manifestations of the 1994 fires in Chelan County are still evident. Standing, dead timber still dominates the landscape in some areas making it hard to escape the presence of the fires. Like most natural resources, forests and woodland are a source of disamenities as well as amenities. My theoretical model illustrates the competing impacts that increases in forest quality and condition have on housing prices, the amenity effect due to increased aesthetics and recreation opportunities and the disamenity of increased fire risk.

The empirical test of this model applied to the 1994 fires in Chelan County yielded mixed results. The estimation results yielded no definitive information on how households value collective risk, represented by vegetation and slope measures. The results did reveal that households place value on living the near the national forest and that this value was unchanged by the fires. The residential housing market in Chelan reacted to the loss of forest amenity, although the impact was brief and depends on the size of the surrounding neighborhood chosen for the collective risk proxies. The effect of the fires on risk perceptions of property damage was more lasting, based on results from previous research on the behavior of risk perceptions in the presence of new information and the analysis of the coefficients for a fire-resistant roof. Perceived risk of property damage was initially understated, then increased for roughly two years following the fires. I argue that the fires themselves, the media and educational programs aimed at homeowners, delivered the increase in information about risk. The reason for the subsequent decline in subjective risk and the willingness to pay for a fire-resistant roof is unclear, but suggests either a risk threshold or a lack or awareness associated with a declining level of information. The message for policy makers is that educational programs directed at households may have little impact if the presence of risk thresholds result in very low perceived risk levels at very high and very low levels of information. If awareness is the issue, education can be successful with sufficient volume and a sustained effort.

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VIII. APPENDIX

Derivation of the Expected Marginal Utility of Income:

An alternate expression for (22) is to set up the Lagrangian, incorporating the expected utility framework:

$$L = \begin{array}{l} \alpha^S\{v^S + \lambda^S(Y^S - X - P_H)\} \\ + \alpha^C\{v^C + \lambda^C(Y^C - X - P_H)\} \\ + (1-\alpha^S - \alpha^C)\{v + \lambda(Y - X - P_H)\} \end{array}$$

where λ^S, λ^C, and λ are the marginal utilities of income in the property damage, community damage, and no wildfire states respectively. The first-order condition with respect to the numeraire good X is

$$\frac{\partial L}{\partial X} = \alpha^S(v_X^f + \lambda^S) + \alpha^C(v_X^C + \lambda^C) + (1-\alpha^S-\alpha^C)(v_X + \lambda) = 0 .$$

Rearranging terms,

$$\alpha^S v_X^S + \alpha^C v_X^C + (1-\alpha^S-\alpha^C)v_X = \alpha^S\lambda^S + \alpha^C\lambda^C + (1-\alpha^S-\alpha^C)\lambda .$$

The expected marginal utility of the numeraire good X is equal to the expected marginal utility of income.

Additional Estimations

These more complex estimations supplement the results presented in Tables 18-21, interacting the vegetation and slope variables with the sales date dummies.

Table 23: OLS regression results of complex model using 90m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.5625	0.3009	475.6691	0.0000*
ln_acres	0.0655	0.0108	36.8749	0.0000*
ln_sq_ft	0.4926	0.0187	693.6928	0.0000*
ln_age	-0.0595	0.0045	176.6814	0.0000*
oth_struct	0.1764	0.0511	11.8919	0.0006*
att_gar	0.1296	0.0119	118.5211	0.0000*
det_gar	0.0840	0.0134	39.4699	0.0000*
deck_porch	0.1011	0.0113	79.7195	0.0000*
patio_carport	0.0514	0.0105	23.9063	0.0000*
unfin_bsmnt	0.0656	0.0109	36.5573	0.0000*
fin_bsmnt	0.1880	0.0115	267.9852	0.0000*
hot_tub	0.0642	0.0493	1.6962	0.1928
fireplace	0.0988	0.0107	85.5872	0.0000*
waterfront	0.7859	0.0569	190.8761	0.0000*
prim_mobile	-0.5070	0.0325	243.9392	0.0000*
perc_white	0.0019	0.0018	1.0741	0.3000
ln_med_inc	0.1152	0.0308	13.9673	0.0002*
road	0.0075	0.0047	2.5690	0.1090
sd922	0.1152	0.0602	3.6627	0.0556**
sd931	0.2442	0.0635	14.7922	0.0001*
sd932	0.2258	0.0601	14.1330	0.0002*
sd941	0.3338	0.0563	35.1244	0.0000*
sd942	0.3188	0.0854	13.9403	0.0002*
sd951	0.1998	0.1015	3.8760	0.0490*
sd952	0.3266	0.0859	14.4698	0.0001*
sd961	0.2553	0.0969	6.9439	0.0084*
sd962	0.5033	0.0733	47.1837	0.0000*
roof921	-0.1243	0.0410	9.1986	0.0024*
roof922	-0.1201	0.0383	9.8253	0.0017*
roof931	-0.1875	0.0395	22.5325	0.0000*
roof932	-0.0831	0.0379	4.8087	0.0283*
roof941	-0.1356	0.0326	17.3202	0.0000*
roof942	-0.0842	0.0373	5.0838	0.0242*
roof951	-0.0910	0.0454	4.0135	0.0451*
roof952	-0.0284	0.0356	0.6357	0.4253
roof961	0.0195	0.0496	0.1551	0.6937
roof962	-0.1462	0.0269	29.5104	0.0000*
nat_for_dist	-0.0091	0.0047	3.7628	0.0524**
nat_for_dist942	-0.0017	0.0090	0.0361	0.8492
nat_for_dist951	0.0082	0.0131	0.3952	0.5296
nat_for_dist952	0.0035	0.0097	0.1339	0.7144
nat_for_dist961	0.0239	0.0088	7.4030	0.0065*
nat_for_dist962	0.0132	0.0093	1.9972	0.1576

Table 23 (cont'd): OLS regression results of complex model using 90m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
fire_dist	-0.0041	0.0011	13.0074	0.0003*
fire_dist942	-0.0007	0.0024	0.0957	0.7571
fire_dist951	0.0052	0.0035	2.1918	0.1387
fire_dist952	-0.0009	0.0028	0.0969	0.7556
fire_dist961	-0.0050	0.0028	3.2751	0.0703**
fire_dist962	-0.0048	0.0022	4.7309	0.0296*
egreen921	-0.0691	0.1270	0.2957	0.5866
egreen922	-0.0314	0.1257	0.0625	0.8026
egreen931	-0.2557	0.1460	3.0660	0.0799**
egreen932	-0.1514	0.1048	2.0880	0.1485
egreen941	-0.0927	0.1185	0.6128	0.4337
egreen942	-0.1118	0.1051	1.1320	0.2873
egreen951	-0.1313	0.1375	0.9111	0.3398
egreen952	-0.0223	0.1120	0.0398	0.8419
egreen961	0.1243	0.1405	0.7833	0.3761
egreen962	-0.0428	0.0935	0.2094	0.6472
shrub921	0.0891	0.0979	0.8284	0.3627
shrub922	-0.1838	0.1289	2.0335	0.1539
shrub931	0.0635	0.1107	0.3291	0.5662
shrub932	-0.0697	0.0915	0.5805	0.4461
shrub941	-0.0641	0.0901	0.5066	0.4766
shrub942	-0.1389	0.1045	1.7667	0.1838
shrub951	-0.0766	0.1746	0.1924	0.6609
shrub952	0.0729	0.1103	0.4369	0.5086
shrub961	-0.0051	0.0955	0.0029	0.9570
shrub962	0.0987	0.0965	1.0459	0.3064
grass921	0.1984	0.1797	1.2193	0.2695
grass922	-0.1922	0.1269	2.2927	0.1300
grass931	0.0846	0.1937	0.1905	0.6625
grass932	0.1197	0.0959	1.5573	0.2121
grass941	-0.1392	0.1408	0.9778	0.3228
grass942	0.0399	0.1015	0.1542	0.6945
grass951	-0.1535	0.1755	0.7658	0.3815
grass952	-0.0116	0.1378	0.0071	0.9327
grass961	0.1017	0.1013	1.0091	0.3151
grass962	-0.1589	0.1236	1.6538	0.1984
slope921	0.0034	0.0077	0.2005	0.6543
slope922	0.0067	0.0056	1.4073	0.2355
slope931	-0.0151	0.0109	1.9156	0.1663
slope932	0.0003	0.0047	0.0040	0.9495
slope941	-0.0157	0.0077	4.1816	0.0409*

Table 23 (cont'd): OLS regression results of complex model using 90m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
slope942	-0.0037	0.0062	0.3545	0.5516
slope951	0.0044	0.0126	0.1238	0.7250
slope952	-0.0085	0.0056	2.2597	0.1328
slope961	0.0031	0.0060	0.2591	0.6108
slope962	-0.0219	0.0090	5.9171	0.0150*
veg_slope921	0.0020	0.0111	0.0333	0.8553
veg_slope922	0.0045	0.0085	0.2754	0.5998
veg_slope931	0.0150	0.0151	0.9928	0.3190
veg_slope932	0.0067	0.0080	0.7021	0.4021
veg_slope941	0.0229	0.0102	5.0037	0.0253*
veg_slope942	0.0135	0.0086	2.4914	0.1145
veg_slope951	0.0034	0.0162	0.0450	0.8320
veg_slope952	0.0063	0.0101	0.3871	0.5338
veg_slope961	-0.0015	0.0101	0.0226	0.8804
veg_slope962	0.0263	0.0116	5.1460	0.0233*

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720
R^2 = .6203
adjusted R^2 = .6122

Table 24: OLS regression results of complex model using 190m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.6275	0.3036	476.4294	0.0000 *
ln_acres	0.0666	0.0109	37.4186	0.0000 *
ln_sq_ft	0.4911	0.0188	682.9366	0.0000 *
ln_age	-0.0597	0.0045	177.6127	0.0000 *
oth_struct	0.1725	0.0516	11.1915	0.0008 *
att_gar	0.1292	0.0119	117.3983	0.0000 *
det_gar	0.0853	0.0133	41.0002	0.0000 *
deck_porch	0.1015	0.0113	80.0586	0.0000 *
patio_carport	0.0515	0.0106	23.7496	0.0000 *
unfin_bsmnt	0.0664	0.0108	37.6183	0.0000 *
fin_bsmnt	0.1873	0.0114	268.7478	0.0000 *
hot_tub	0.0627	0.0494	1.6121	0.2042
Fireplace	0.0973	0.0107	83.0993	0.0000 *
waterfront	0.7844	0.0570	189.0667	0.0000 *
prim_mobile	-0.5049	0.0322	245.3260	0.0000 *
perc_white	0.0018	0.0018	0.9207	0.3373
ln_med_inc	0.1112	0.0311	12.8187	0.0003 *
road	0.0074	0.0047	2.4590	0.1169
sd922	0.1105	0.0628	3.0907	0.0787 **
sd931	0.2588	0.0634	16.6490	0.0000 *
sd932	0.2310	0.0623	13.7589	0.0002 *
sd941	0.3450	0.0585	34.7298	0.0000 *
sd942	0.3358	0.0884	14.4130	0.0001 *
sd951	0.2144	0.1064	4.0558	0.0440 *
sd952	0.3068	0.0897	11.6882	0.0006 *
sd961	0.2479	0.0986	6.3145	0.0120 *
sd962	0.5057	0.0752	45.2289	0.0000 *
roof921	-0.1242	0.0408	9.2613	0.0023 *
roof922	-0.1138	0.0384	8.8034	0.0030 *
roof931	-0.1854	0.0394	22.1912	0.0000 *
roof932	-0.0871	0.0380	5.2444	0.0220 *
roof941	-0.1361	0.0321	17.9577	0.0000 *
roof942	-0.0843	0.0378	4.9808	0.0256 *
roof951	-0.0964	0.0454	4.5140	0.0336 *
roof952	-0.0327	0.0357	0.8348	0.3609
roof961	0.0186	0.0495	0.1413	0.7070
roof962	-0.1545	0.0270	32.8060	0.0000 *
nat_for_dist	-0.0106	0.0047	5.1748	0.0229 *
nat_for_dist942	-0.0022	0.0088	0.0642	0.8000
nat_for_dist951	0.0086	0.0131	0.4347	0.5097
nat_for_dist952	0.0067	0.0096	0.4892	0.4843
nat_for_dist961	0.0266	0.0088	9.0551	0.0026 *
nat_for_dist962	0.0152	0.0094	2.6290	0.1049

Table 24 (cont'd): OLS regression results of complex model using 190m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
fire_dist	-0.0043	0.0012	13.7523	0.0002 *
fire_dist942	-0.0007	0.0024	0.0896	0.7647
fire_dist951	0.0053	0.0035	2.2659	0.1322
fire_dist952	-0.0003	0.0028	0.0117	0.9138
fire_dist961	-0.0049	0.0027	3.3173	0.0686 **
fire_dist962	-0.0046	0.0023	4.2562	0.0391 *
egreen921	-0.0827	0.1359	0.3702	0.5429
egreen922	-0.0972	0.1438	0.4576	0.4987
egreen931	-0.2994	0.1554	3.7112	0.0540 **
egreen932	-0.1499	0.1156	1.6818	0.1947
egreen941	-0.1878	0.1400	1.7992	0.1798
egreen942	-0.1579	0.1181	1.7897	0.1810
egreen951	-0.1577	0.1521	1.0747	0.2999
egreen952	0.0691	0.1282	0.2904	0.5900
egreen961	0.1448	0.1527	0.8988	0.3431
egreen962	-0.0126	0.1114	0.0127	0.9103
shrub921	0.0457	0.1407	0.1057	0.7451
shrub922	-0.2072	0.1307	2.5121	0.1130
shrub931	0.2405	0.1251	3.6941	0.0546 **
shrub932	-0.1101	0.1096	1.0075	0.3155
shrub941	-0.1482	0.1288	1.3225	0.2501
shrub942	-0.1374	0.1325	1.0761	0.2996
shrub951	-0.0332	0.2090	0.0253	0.8736
shrub952	0.0852	0.1302	0.4283	0.5128
shrub961	-0.0235	0.1102	0.0455	0.8310
shrub962	0.1085	0.1243	0.7623	0.3826
grass921	0.1319	0.2600	0.2575	0.6119
grass922	-0.2731	0.1737	2.4720	0.1159
grass931	-0.0552	0.2387	0.0536	0.8170
grass932	0.1912	0.1279	2.2343	0.1350
grass941	-0.0830	0.1630	0.2594	0.6105
grass942	0.0241	0.1331	0.0328	0.8563
grass951	-0.2415	0.2302	1.1005	0.2942
grass952	0.0220	0.1820	0.0146	0.9038
grass961	0.0576	0.1329	0.1881	0.6645
grass962	-0.1104	0.1597	0.4778	0.4894
slope921	0.0077	0.0080	0.9304	0.3348
slope922	0.0153	0.0071	4.6517	0.0310 *
slope931	-0.0191	0.0113	2.8376	0.0921 **
slope932	0.0039	0.0068	0.3320	0.5645
slope941	-0.0123	0.0093	1.7379	0.1874
slope942	-0.0045	0.0072	0.3899	0.5324

Table 24 (cont'd): OLS regression results of complex model using 190m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
slope951	0.0031	0.0148	0.0427	0.8363
slope952	-0.0039	0.0074	0.2803	0.5965
slope961	0.0062	0.0073	0.7267	0.3940
slope962	-0.0201	0.0087	5.3511	0.0207 *
veg_slope921	0.0022	0.0138	0.0249	0.8747
veg_slope922	-0.0040	0.0110	0.1308	0.7176
veg_slope931	0.0171	0.0169	1.0319	0.3097
veg_slope932	0.0015	0.0109	0.0197	0.8884
veg_slope941	0.0212	0.0125	2.8976	0.0887 **
veg_slope942	0.0146	0.0104	1.9714	0.1603
veg_slope951	0.0062	0.0193	0.1027	0.7487
veg_slope952	-0.0021	0.0136	0.0233	0.8786
veg_slope961	-0.0041	0.0126	0.1046	0.7464
veg_slope962	0.0217	0.0123	3.0945	0.0786 **

note: * denotes significance at 5%, ** denotes significance at 10%

n = 4,720
R^2 = .6204

adjusted R^2 = .6124

Table 25: OLS regression results of complex model using 510m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
Intercept	6.7258	0.3122	463.9732	0.0000*
ln_acres	0.0729	0.0111	43.1403	0.0000*
ln_sq_ft	0.4914	0.0187	690.8958	0.0000*
ln_age	-0.0602	0.0045	178.4425	0.0000*
oth_struct	0.1630	0.0522	9.7605	0.0018*
att_gar	0.1286	0.0120	114.8798	0.0000*
det_gar	0.0830	0.0134	38.3525	0.0000*
deck_porch	0.1057	0.0115	85.1170	0.0000*
patio_carport	0.0528	0.0106	24.6194	0.0000*
unfin_bsmnt	0.0682	0.0109	39.1706	0.0000*
fin_bsmnt	0.1897	0.0114	277.5238	0.0000*
hot_tub	0.0675	0.0493	1.8733	0.1711
fireplace	0.0983	0.0106	85.2131	0.0000*
waterfront	0.7733	0.0573	182.1069	0.0000*
prim_mobile	-0.5049	0.0325	241.8733	0.0000*
perc_white	0.0004	0.0019	0.0420	0.8376
ln_med_inc	0.1196	0.0324	13.5931	0.0002*
road	0.0051	0.0048	1.1389	0.2859
sd922	0.1187	0.0721	2.7107	0.0997**
sd931	0.2483	0.0704	12.4338	0.0004*
sd932	0.2113	0.0663	10.1600	0.0014*
sd941	0.3171	0.0647	24.0306	0.0000*
sd942	0.3434	0.0996	11.8831	0.0006*
sd951	0.1156	0.1147	1.0157	0.3135
sd952	0.2655	0.0936	8.0454	0.0046*
sd961	0.2369	0.1006	5.5393	0.0186*
sd962	0.4708	0.0813	33.4984	0.0000*
roof921	-0.1257	0.0424	8.7726	0.0031*
roof922	-0.1113	0.0398	7.8334	0.0051*
roof931	-0.1942	0.0389	24.9537	0.0000*
roof932	-0.0902	0.0373	5.8512	0.0156*
roof941	-0.1345	0.0322	17.4899	0.0000*
roof942	-0.0911	0.0386	5.5555	0.0184*
roof951	-0.0946	0.0433	4.7655	0.0290*
roof952	-0.0298	0.0346	0.7424	0.3889
roof961	0.0235	0.0506	0.2152	0.6427
roof962	-0.1537	0.0265	33.5545	0.0000*
nat_for_dist	-0.0122	0.0047	6.6579	0.0099*
nat_for_dist942	-0.0022	0.0089	0.0639	0.8005
nat_for_dist951	0.0099	0.0133	0.5583	0.4549
nat_for_dist952	0.0078	0.0101	0.5892	0.4427
nat_for_dist961	0.0274	0.0091	8.9853	0.0027*
nat_for_dist962	0.0148	0.0092	2.6068	0.1064

Table 25 (cont'd): OLS regression results of complex model using 510m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
fire_dist	-0.0045	0.0013	12.7056	0.0004*
fire_dist942	-0.0011	0.0026	0.1773	0.6737
fire_dist951	0.0070	0.0036	3.7491	0.0528**
fire_dist952	0.0004	0.0028	0.0157	0.9003
fire_dist961	-0.0056	0.0027	4.3999	0.0359*
fire_dist962	-0.0045	0.0024	3.6099	0.0574**
egreen921	-0.1024	0.1334	0.5888	0.4429
egreen922	-0.0844	0.1470	0.3295	0.5659
egreen931	-0.2282	0.1831	1.5521	0.2128
egreen932	-0.0698	0.1077	0.4198	0.5170
egreen941	-0.2165	0.1819	1.4163	0.2340
egreen942	-0.2271	0.1535	2.1879	0.1391
egreen951	0.0302	0.1532	0.0388	0.8439
egreen952	0.1563	0.1477	1.1193	0.2901
egreen961	0.0419	0.1554	0.0728	0.7873
egreen962	0.0364	0.1347	0.0732	0.7867
shrub921	0.0535	0.1862	0.0825	0.7740
shrub922	-0.0556	0.1689	0.1084	0.7420
shrub931	0.3536	0.1509	5.4952	0.0191*
shrub932	-0.0674	0.1174	0.3299	0.5657
shrub941	-0.2053	0.1669	1.5142	0.2185
shrub942	-0.1374	0.1442	0.9085	0.3405
shrub951	-0.0203	0.2198	0.0085	0.9264
shrub952	0.0607	0.1844	0.1084	0.7419
shrub961	-0.0852	0.1480	0.3319	0.5646
shrub962	0.1524	0.1472	1.0714	0.3006
grass921	0.1234	0.2853	0.1871	0.6654
grass922	-0.2601	0.2522	1.0642	0.3023
grass931	-0.2731	0.3139	0.7568	0.3843
grass932	0.3235	0.1901	2.8949	0.0889**
grass941	0.1513	0.2088	0.5246	0.4689
grass942	-0.1082	0.1844	0.3441	0.5574
grass951	-0.0053	0.2995	0.0003	0.9859
grass952	0.1366	0.2159	0.4006	0.5268
grass961	-0.1180	0.2230	0.2798	0.5969
grass962	-0.0309	0.2244	0.0189	0.8906
slope921	-0.0009	0.0106	0.0075	0.9310
slope922	0.0006	0.0115	0.0031	0.9559
slope931	-0.0217	0.0127	2.9290	0.0870**
slope932	0.0011	0.0089	0.0157	0.9002
slope941	-0.0103	0.0113	0.8173	0.3660
slope942	-0.0108	0.0092	1.3960	0.2374

Table 25 (cont'd): OLS regression results of complex model using 510m neighborhood. Dependent variable is the natural log of price, *ln_P*.

Variable	Estimate	Asymp Std Err	Chi Square	p > Chi Square
slope951	0.0144	0.0127	1.2986	0.2545
slope952	-0.0044	0.0082	0.2939	0.5877
slope961	0.0054	0.0079	0.4573	0.4989
slope962	-0.0150	0.0071	4.5093	0.0337*
veg_slope921	0.0062	0.0139	0.1965	0.6576
veg_slope922	-0.0023	0.0139	0.0272	0.8690
veg_slope931	0.0192	0.0201	0.9132	0.3393
veg_slope932	-0.0053	0.0136	0.1518	0.6968
veg_slope941	0.0124	0.0149	0.6919	0.4055
veg_slope942	0.0221	0.0132	2.7779	0.0956**
veg_slope951	-0.0180	0.0172	1.0950	0.2954
veg_slope952	-0.0073	0.0139	0.2781	0.5979
veg_slope961	0.0004	0.0118	0.0010	0.9746
veg_slope962	0.0089	0.0103	0.7402	0.3896

note: * denotes significance at 5%, ** denotes significance at 10%
n = 4,720
R^2 = .6185
adjusted R^2 = .6104