WILDFIRE IN ALASKA: THE ECONOMIC ROLE OF FUEL TREATMENTS AND HOMEOWNER PREFERENCES IN THE WILDLAND URBAN INTERFACE

By

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Abstract

The challenges of increased temperatures, drier fuels and more intense wildfires are having a detrimental effect on Alaskans, especially those who live in the wildland urban interface. This area is defined by open wildlands being directly adjacent to homeowners. Human safety and property are exposed to increasing risk from these wildfires as climate-based changes affect the state. The rising costs of suppressing wildfires necessitate exploring potential solutions to minimize the impact on the state population and budget. The purpose of this study is to analyze the feasibility of fuel treatments to reduce suppression costs and provide incentives to private homeowners to create safer property spaces. An electronic survey and choice experiment were administered to 388 Alaskan homeowners to measure willingness-to-pay for different attributes associated with wildfire risk reduction variables, including nearby fuel treatments and overall neighborhood participation. Expenditure data were collected for large Alaskan wildfires between 2007 and 2015. An econometric cost model was developed to estimate the effect of nearby fuel treatments on final wildfire suppression expenditures. In both scenarios, there was a limited effect from public land fuel treatments on homeowner preferences and total suppression costs. Homeowners had a strong preference for thinned fuel treatments but did not prefer clear-cut tracts of land, even when compared to doing nothing at all. The survey provided significant insight into the preferences of Alaskan homeowners, including altruistic behavior, free riding behavior, self-assessment of risk, and the amenity values of surrounding vegetation. The costs of large Alaskan wildfires in the data set was mainly driven by protection level and number of burn days, and not by the presence or potential utilization of fuel treatments.

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Chapter 1 Introduction

The state of Alaska is currently facing an unprecedented budget crisis. Critical services are in jeopardy as the price of oil has significantly dropped since the second half of 2014. While the state mobilizes to address their immediate and essential needs, long term planning is required to minimize future budgetary challenges. One significant area of concern is funding for wildfire suppression. The state Department of Forestry is responsible for protecting life and property in state managed lands, as well as assist in that responsibility on federal lands. These lands are often adjacent to private homeowners, and these large communities are particularly vulnerable to catastrophic loss from an immense and uncontrollable wildfire. The probability of these wildfires occurring is increasing, as wildfires have been shown to be increasing in both frequency and severity in Alaskan boreal forests (Kasischke & Turetsky 2006). Suppression costs are expected to be between one and two billion dollars over the next century and averaging $60 million per year (Melvin et al. 2017). While these numbers may seem reasonable for such a vital service, it represents a very large expenditure, and an even larger expense when viewed from a per capita perspective. Because of this, research must be done to examine potential budgetary efficiencies and look for avenues to respond to this potential expenditure increase.

One potentially effective method of reducing suppression costs are the use of fuel treatments (Saperstein et al. 2014). Fuel treatments are areas where large portions of flammable vegetative biomass are removed from strategic wildfire suppression locations. These fuel treatments can be costly and need consistent maintenance. However, even older fuel treatments can significantly mitigate wildfire behavior (Little et al. 2018). There are also different types of fuel treatments, each with different advantages and weaknesses. Thinned fuel treatments focus on reducing the bulk of the flammable fuels from the forest understory, leaving the tree structures mainly intact. These are much more expensive than clear cutting treatments and have the potential to cost upwards of $8,000 per acre in 2019 dollars (St. Clair 2006). From a budget standpoint, the costs associated with these fuel breaks need to at least equal the saved suppression costs from their use. Another effective method to address this issue is to examine community wide fuel reduction on private lands. Homeowner actions reduce community level wildfire risk and can lessen the pressure on land management agencies to protect vulnerable communities. It becomes necessary to understand the incentives and factors that determine the behavior of these homeowners that are especially susceptible to wildfire. Understanding the effectiveness of fuel treatments and homeowner incentives forms the basis of the presented work and is assessed over the next three chapters.

Chapter 2 and 3 analyze an electronic survey, but from very different perspectives. Chapter 2 approaches the survey from a more traditional social science perspective and looks at multiple choice and multi-select questions to ascertain stated homeowner preferences. Land management agencies often place fuel treatments in locations for suppression strategy alone and sometimes fail to assess how this changes private homeowner behavior. Previous studies have shown that these fuel treatments create the illusion that homeowners are adequately protected from wildfire risk and acts as a disincentive to homeowners taking actions that decrease risk on their own property (Prante et al. 2011, Talberth et al. 2006). These private land actions can have significant impact to community level wildfire risk (Butry and Donovan 2008) and is generally under provided in many Alaskan communities (Brenkert-Smith et al. 2006). Private homeowner risk mitigating activity should then be viewed similarly to fuel treatments in their effectiveness to reduce risk to homeowner property from wildfire. While it will not have the same budgetary impacts as public land fuel treatments, these changes could create more wildfire resilient communities and potentially share the burden of community wide wildfire risk reduction.

Homeowners are susceptible to various issues when determining the level of wildfire risk reducing activities they will pursue. Homeowners often weight the amenity and privacy values of flammable fuels on their property with the risk reduction associated with removing those fuels. These values drive the under provision of private risk mitigation activities (Kobayashi et al. 2010, Paveglio et al. 2016). Alaskan homeowners also have permafrost soils to contend with, as any threat to those soils threatens the structural integrity of structures built on them. In this context, the shade provided by flammable fuels is not only a preference, but a necessity for the stability of their homes. Any failure of objective information being disseminated to homeowners has detrimental consequences on the actions needed to reduce wildfire risk. Subjective assessment of wildfire risk is also a noteworthy driver risk (Brenkert-Smith et al. 2012), as it was found to be a better indicator of homeowner risk mitigation actions than having previous wildfire experience (Martin et al. 2009). The survey chapter addresses many of these themes, including the effects of free-riding behavior, insurance, and defensible space have on mitigation actions on private lands.

Chapter 3 addresses many of the same themes that are presented in chapter 2. The electronic survey also included a choice experiment to more quantitatively capture willingness-to-pay (WTP) for risk reduction variables. Specifically, the choice experiment estimates WTP for neighbors reducing fuels on their property, public land fuel treatments, and direct risk reductions to both the respondent and their neighbors. Choice experiments isolate individual preferences for variable attributes by comparing respondent choices. By repeating these choices and including more respondents, preferences for variable attributes emerge and are quantified monetarily. The WTP estimates provide insight into potential avenues to increase homeowner risk mitigation behavior and how land management agencies can best contribute to preferred behaviors. An adaptive method was used which both allowed for on-the-fly choice set design, as well as Hierarchical Bayesian analysis of the data. This chapter also used survey responses to examine how WTP estimates change based on location (borough), subjective and objective risk, previous experience with wildfire, and insurance considerations.

Chapter 4 attempts to assess the problem most directly with an econometric cost model estimating factors that affect total suppression costs. Wildfire costs have increased over time since the 1970's (Calkin et al. 2005, Gorte 2013) and are expected to continue increasing due to climate-based changes and more intense fires. These models can be difficult to analyze because of the endogeneity (reverse causality) present in suppression variables. The inclusion of endogenous variables requires the careful use of instrumental variables to accurately estimate these effects. The analysis of these variables (endogenous and instrumental) are useful on its own and can provide useful evidence for future studies. The primary variable of interest is fuel treatments, as this variable will determine the effect these treatments have on suppression costs. The number of control variables included in the cost models are wildfire protection zone, wildfire cause (human or lightning), year of fire, acres burned, days burning, slope, elevation, fuel type, and other climate variables.

The work presented here builds from previous literature but makes its own significant contribution to the larger body of research. Discreet choice experiments are not ubiquitous in natural resource economic research, especially in its application to homeowner's incentives regarding wildfire risk reduction. By constructing the choice experiment variables such that homeowner's risk and neighbor's risk were disconnected, it allows us to investigate themes such as altruism, free riding, and vegetative amenity values in a novel way. The population surveyed also allows us to investigate WUI communities that have unique challenges and characteristics, such as permafrost, subarctic temperatures and lack of infrastructure. Combining willingness-to-pay estimates with survey and sociodemographic responses allows for the analysis of distinct groups that innovatively explore these homeowner preferences. As with any new research, a careful balance between novelty and supporting literature is critical when investigating significant but original problems.

As with any research, this work still leaves many questions unanswered. Future studies should leverage increases in wildfire data for both survey and econometric purposes to more completely inform these models. Evacuations due to imminent wildfire provide an external event that may influence homeowner responses in affected areas. For example, the Shovel Creek fire of 2019 forced evacuations in the area north west of Fairbanks. Because this area was surveyed in 2016, follow up surveys can identify how respondent preferences have changed. There is still much to investigate when examining the effectiveness of fuel treatments in Alaska. Please note that this work is formatted as a manuscript and as such, the chapters will have different structure based on the proposed publication setting.

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Chapter 2 Homeowner Preferences of Wildfire Risk Mitigation in the Alaskan Wildland Urban Interface - Selected Survey Results[1]

Abstract

Alaska has the unique distinction of being the largest state in the US, as well as one of the least populated. This gives rise to increased expansion of homeowners into the Wildland Urban Interface (WUI). Probabilistic wildfire events are examined from the perspective of a natural hazard. Common hazard themes are explored to study the human dimension of these wildfire events. These themes include risk perception, insurance, and common incentives for risk mitigation activities. We also compare how two different Alaskan boroughs differ in this context. We examine how homeowners in different wildfire risk areas make different mitigation action decisions. There is evidence of risk perception issues across both boroughs, with homeowners regularly misidentifying their own objective wildfire risk. There is also evidence that the amenity values associated with flammable fuels may disincentive homeowner participation in wildfire risk reducing activities. Homeowners are not influenced by risk perception when deciding to purchase homeowner's insurance. Lastly, land management agency participation in fuel reduction was not seen as a preferred method of risk mitigation, as community capacity building, increased participation and direct payments were much more preferred.

2.1 Introduction

The wildland urban interface (WUI) is an important piece in the context of the human impacts from wildfire. The formal definition from Radeloff et al. (2005) is that the Wildland Urban Interface is "the area where houses meet or intermingle with undeveloped wildland vegetation." Some Alaskan WUI areas are sparsely populated, with small communities being directly adjacent to dense wild forests. This in turn increases the risk homeowners face from wildfire, both in wildfire attacking their individual lot lines, and the risk of home structure ignition. When a wildfire event begins close to these WUI communities, there may be little time for suppression efforts. The probabilistic nature of wildfire also makes it difficult to anticipate how they will threaten individual WUI communities. The focus on building adaptive capacity in these neighborhoods then lay within a pre-suppression effort that can handle a wide array of wildfire threats. It has been shown that pre-suppression risk mitigation efforts can reduce the overall

[1] This chapter is currently being prepared externally for academic journal publication. Other authors on that manuscript include Joseph Little (University of Alaska Fairbanks), Stacy Drury (USDA - US Forest Service), Randi Jandt (University of Alaska Fairbanks) and Brock Lane (University of Alaska Fairbanks).

impacts and costs of wildfire (Lankoande and Yoder 2006). Individual homeowners can act on their own property to combat this potential threat and to decrease their own risk, exclusive of any other external risk mitigation activity. However, these actions can also have a spatial benefit beyond the individual homeowner's lot lines. Communal risk reduction can be maximized from the optimal placement of pre-suppression efforts (Butry and Donovan 2008). Community level programs can help with these large-scale examinations of WUI communities in high-risk areas. They can increase wildfire risk information, increase neighbor interactions, and help plan and execute suppression actions on private homeowner lands. These programs rely on a thorough understanding of what incentivizes homeowners to take risk mitigation actions and what may be stopping them from participating on a community wide scale. There is also a need to examine how different groups of people in high-risk WUI communities behave based on the distribution of risk or presence of natural amenities (Champ et al. 2013). This paper aims to discuss these topics via a survey of homeowners in two Alaskan Boroughs on homeowner participation in wildfire risk reduction activities.

The state of Alaska is distinctive in many regards, but the size of the state creates wildfire risk scenarios that produce difficult suppression situations. The small population of the state and the spatial distribution of its residents increase the proportion of population living in WUI locations. The state is in a challenging situation where they may lack key infrastructure to provide the best suppression protection, and limited resources to provide optimal pre-suppression actions. It is then critical for the state to address these issues and identify how to optimally leverage state resources to reduce the risk of loss from wildfire events. It is also important to understand how homeowners respond to land management agency (LMA) action. Alaskan homeowners may respond to these actions with their own risk mitigation actions, while others may acquire a misguided sense of security from reduced community wildfire risk. Before LMAs act, it is important to know just how homeowners will respond and how those actions fit into the larger conversation of community wildfire risk reduction.

Alaska provides an interesting spatial backdrop with respect to risk perception. Alaska is the most sparsely populated state in the US. In 2017, there were 739,795 people living within the state area of 663,300 square miles. Not only does this drastically increase the probability of naturally occurring wildfire affecting the state, but potentially increases the proportion of residents who are in WUI locations. There are only a handful of population centers, but these include the Anchorage/Mat-Su area, the Fairbanks North Star Borough (FNSB), the Kenai Peninsula Borough (KPB), and the southeast (Juneau/Ketchikan). The Anchorage/Mat-Su area is by far the largest and most densely populated, with about half of the total state residents, while the southeast is a chain of islands and peninsulas. The other two, FNSB and the KPB have expansive WUI communities and are particularly at risk for destructive wildfires. However, because most residents huddle within population centers within boroughs, there may be a false perception of safety within those communities. Based on Community Wildfire Protection Plans (CWPPs) that were developed for boroughs wildfire preparedness, virtually the entire inhabited coast of the KPB has an "extreme" wildfire risk rating. This is primarily due to the surrounding wildlands, fuel types and densities that could make a large wildfire catastrophic to those communities. But these aggregate risks may be lost from view from the perspective of a homeowner surrounded by homes in a large development. Residents in the KPB were found to reduce their risk perception related to fuels and proximity hazards primarily because of a reduction in spruce bark beetles damaged trees and less experience with previous wildfires (Gordon et al. 2013). While these issues should reduce risk perceptions, it may dominate the conversation, and give residents the false sense of significantly lowered levels of overall wildfire risk.

The objective risk of Alaskan communities is evaluated by borough wide CWPPs. Wildfire suppression agencies and other wildfire experts help guide communities with best practices and risk identification by developing these plans. The plans also define the areas at greatest risk and devise plans to increase adaptive capacity for those living there. The two areas of interest for this study are the Fairbanks-North Star Borough (FNSB) and the Kenai Peninsula Borough (KPB). Each of these areas have CWPPs that are constantly reexamined and updated with the most current and reliable science. Each of these plans define specific areas at risk of wildfire. Their flammable fuel loads and topography partly define the risk these zones. In the FNSB, these boundaries are defined as high, very high and extreme risk of wildfire. The KPB has similar nomenclature, however their boundaries are defined as low, moderate, high and extreme risk of wildfire. For the sake of this analysis, we combine the naming conventions for continuity[2]. These definitions become the objective metric to assess homeowner risk in these boroughs. Both risk zones maps can be seen in figures 2.1 and 2.2.

[2] The KPB naming is changed to reflect the FNSB naming, where the three highest risk zones are defined in the same way as in the FNSB CWPP. The low risk zone is dropped as it has no comparable category in the FNSB CWPP.

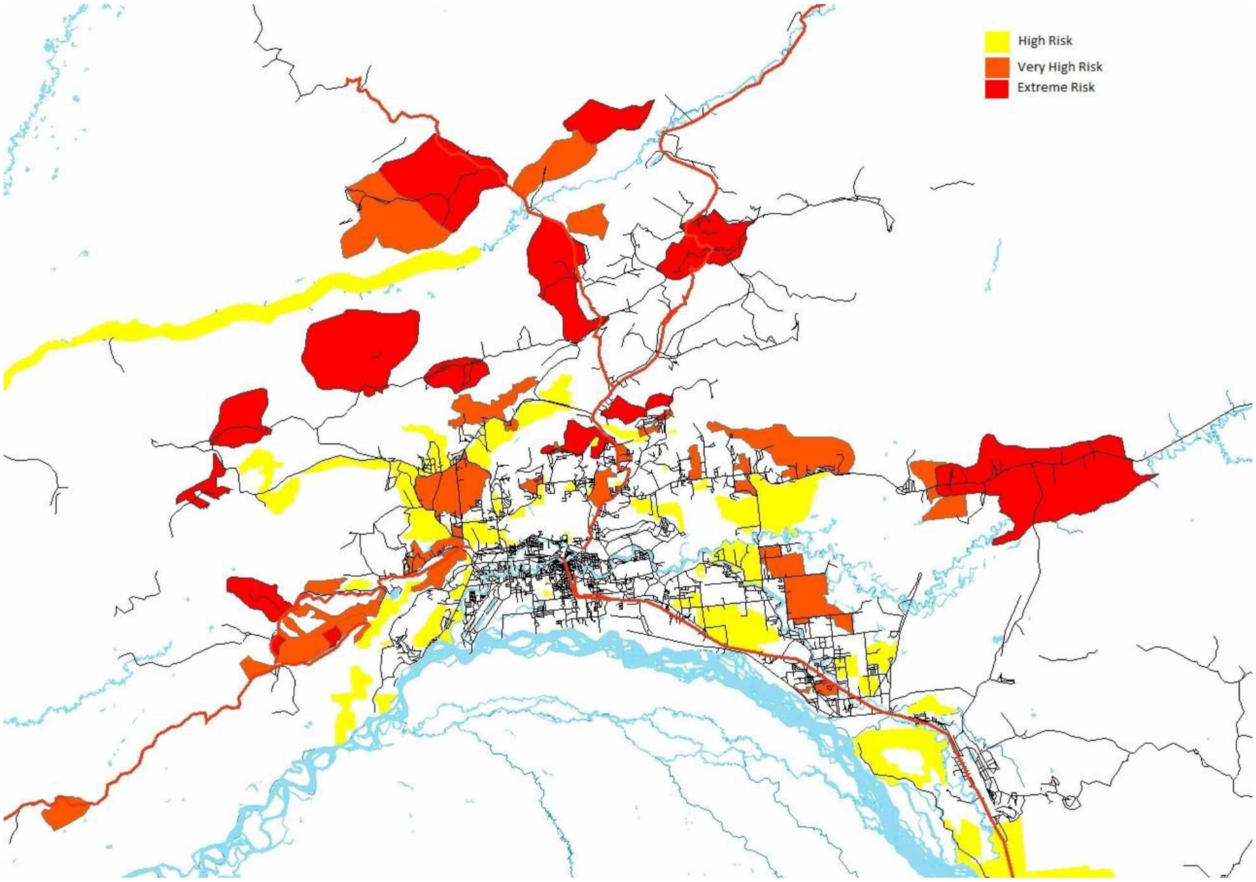

Figure 2.1: Objective risk zones in the Fairbanks-North Star Borough. Areas in yellow are in high risk, orange are in very high risk, and red are in extreme risk. Map generated in ArcMap (GIS).

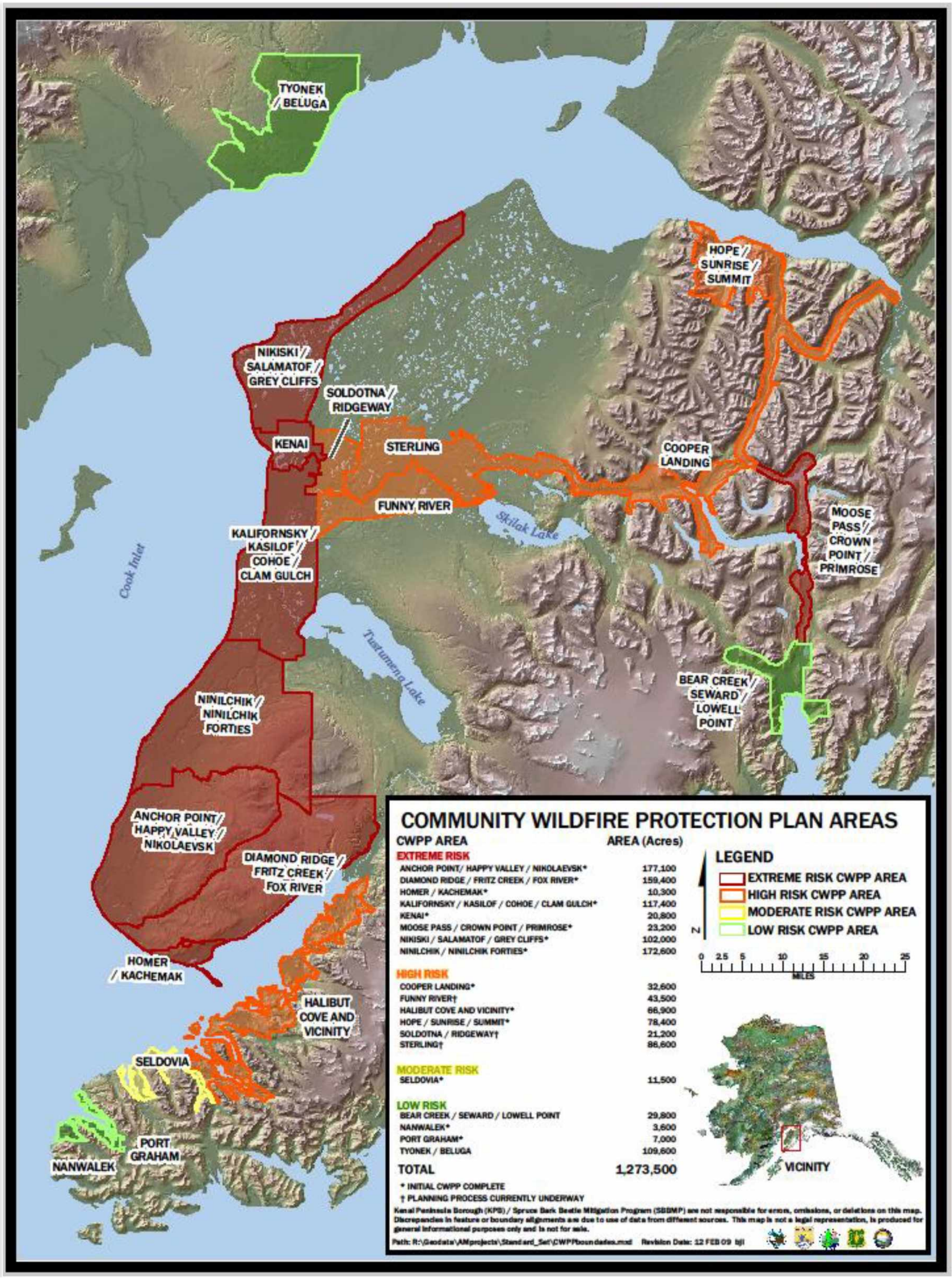

Figure 2.2: Objective risk zones in the Kenai Peninsula Borough. Legend seen below and includes four risk areas, low, moderate, high and extreme risk (Kenai Peninsula Borough 2019).

2.2 Background

2.2.1 Risk Perception

The occurrence of a nearby wildfire may objectively threaten homes in WUI locations. These homeowners can protect themselves by following best practices for the removal of fuels and treatment of flammable vegetation on their property. From a utility maximization standpoint, homeowners are balancing the perceived risk of loss with the direct and indirect costs of these best practices. More formally, the homeowner will act when:

$$U_{\text{risk reduction}} > U_{\text{saved costs}}$$

However, this framework assumes that homeowners are acutely aware of all risks, as well as the fundamental likelihood wildfire will threaten their property. Perfect or even sufficient information is often lacking for many WUI homeowners. Risk perception then becomes a key variable in determining whether these actions take place (Champ et al. 2013). A 2012 study showed that risk perception, specifically questions regarding flammable fuels on the property and overall wildfire risk were statistically significant contributors to mitigation actions being taken on a homeowner's property (Brenkert-Smith et al 2012). This was also studied in-depth by Martin et al. (2009) who found that risk perception was a stronger indicator than previous wildfire experience for mitigation actions. Professional assessments, like those found in CWPPs often diverge from individual, non-expert assessments of overall wildfire risk (Meldrum et al. 2015). This creates a scenario, where objective, professional assessments are not resonating with homeowners, either because of inefficient information channels, or the perceived subjectivity of risk factors. There also seems to be some disconnect between perceived efficacies of mitigation treatments among homeowners (Wilson et al. 2017). Even when actions are taken, subjective assessments of wildfire risk perception can inhibit actual and necessary risk reduction to homeowner land in WUI communities.

2.2.2 Insurance

When a homeowner appropriately assesses risk on their property, they may decide to reduce their risk via mitigation actions. However, this is only one choice out of a complex matrix of decisions that a homeowner may take. Another is to avert monetary loss with homeowner's insurance. While it is often cited as a smaller piece of the decision-making process, institutional factors like homeowner's insurance may be prevalent in those who chose to not partake in mitigation actions (Brenkert et al. 2005). When faced with the decision to pursue mitigation actions or cover loss with insurance premiums, several factors must be analyzed by the decision maker. In perfect information situations, these decisions will depend on the actual probability of risk, cost of mitigation action, discount rates, value of the home, insurance premium costs, and predicted years until occurred loss. In the hazard risk mitigation literature, these values help with internal benefit/cost analysis for individual homeowner decision making (Kunreuther 1996). In this context, the choice that provides the best benefit/cost ratios in the shortest amount of time will be the best objective decision. However, there is rarely a situation in which perfect probability information exists, as much of this information is unavailable for homeowner decision making. Underestimation of probability can drastically skew these internal calculations. As mentioned in the previous section, differences in perceived risk and the probabilistic nature of wildfire can push homeowners into non-optimal situations. From a utility standpoint, a homeowner will choose to insure their home over mitigation actions when

$$U_{\text{risk reduction to covered loss}} > U_{\text{saved premium cost}}$$

This is not to imply that one cannot chose to take on both activities. Non-covered losses may require additional actions that reduce both covered and non-covered losses for those who are more risk averse (Talberth et al. 2006). In that case, the utility drivers of that decision are when

$$U_{\text{risk reduction to covered loss}} + U_{\text{risk reduction to non-covered losses}} > U_{\text{saved premium cost}} + U_{\text{saved mitigation costs}}$$

For these individuals, we would expect a more complex benefit/cost calculation that would include internal valuation of non-covered losses. These decisions are still affected by a difference in perceived and actual risk probabilities. Perceived risk was found to be a major determining factor for homeowners choosing insurance, with those who perceived higher risk consistently being more likely to purchase hazard protection policies (Kunreuther 1996).

2.2.3 Incentivizing Mitigation Actions

While homeowners have complex internal decision-making processes that guide their behavior, external factors may be able to incentivize risk mitigation actions. One such incentive could be the treatment of fuels on nearby public lands. When an LMA chooses to be a participant in the risk mitigation process, it may incentive others to participate. However, there are a few issues when approaching homeowners in this way. The first is that many homeowner's do not believe that there is a requirement for government intervention at all relating to the reduction of private homeowner risk (McCaffrey et al. 2011). When the onus is on the homeowner to mitigate wildfire risk, LMAs may be best served as educators and stewards of their own lands. The second issue that arises, is that there is evidence of a "crowding out" effect, where LMA mitigation actions are perceived to be sufficient, and dissuade homeowners from spending as much as they may need on their own risk mitigation actions (Prante et al. 2011, Talberth et al. 2006). The dissemination of private homeowner actions and contingent policies on

LMA participation seem to reduce this effect. When LMA participation is seen in the larger context of all external participants, this incentivization may be stronger. There is also the potential to leverage the strong social component to incentivize mitigation behavior. Homeowners are more likely to participate in wildfire risk reduction programs when their community is working together and when increasing adaptive capacity to wildfire is the standard (Sturtevant & McCaffrey 2006). Some of the economic decision-making previously discussed may also be abated by highlighting the social advantages of risk mitigation participation. Peer pressure has been shown to be effective at increasing participation of neighborhood wide risk mitigation (McCaffrey et al. 2011), as well as preexisting community institutions (McFarlane et al. 2007).

Even with these incentives, individual level utility maximization and cost minimization may induce free riding behaviors. In this context, free riding behaviors are ones that keep individual costs minimal, while receiving the non-excludable community wide wildfire risk reduction from other homeowner risk mitigation actions. Because community level risk mitigation actions reduce the probability of wildfire interactions, there may be little incentive for everyone to participate, especially when the marginal increase in overall neighborhood risk reduction may not be cost effective. This potentially creates a contradiction where the incentivization of risk reduction activities in some homeowners reduces participation in others. This "wildfire risk mitigation paradox" has been examined and generally shows that these free riding agents contribute to the overall under provision of homeowner participation (Little et al. 2017). Yet again, information sharing becomes a potential tool to combat this paradox, as the development of social capital has been shown to mitigate the negative effects of wildfire risk reduction (Prante et al. 2011). In general, even with the mitigation paradox and crowding out effects, there are many factors that influence the overall adaptive capacity of a community, and care should be taken to leverage variables within communities to maximize effectiveness (Paveglio et al. 2012).

2.2.4 Method

An electronic survey was developed to address a wide range of homeowner preferences. Lighthouse studio (formerly Sawtooth) software was chosen for survey implementation. The software allowed us to create logic gates and pathing to keep the cognitive burden on respondents as low as possible. Questions were multiple choice and multiple selection, with the occasional option for writing in other responses. There were 41 multiple choice/select questions on the survey, with two comment boxes and a supplementary choice experiment which is not included in this analysis. Our sample selection starts with the identification of those homeowners in the high-risk areas of the FNSB and the KPB. Homeowners in these high-risk areas were spatially identified using publicly available tax parcel information. From this expansive list, 1000 homeowners were randomly selected[3] from each borough, with a range of risk zones. Once selected, we followed a modified Dillman survey method to increase our response rate (Hoddinott 1986). An initial postcard invitation helped us identify out of date addresses, and two follow-up letters reminded homeowners of the importance of the project. We also gave the option for a printed survey for those without access to the internet[4]. While not everyone answered all items, a total of 388 homeowners participated in the survey (a response rate of 19.4%). Various statistical tests were used on the resulting data, including t-tests, ANOVA and χ^2 tests. The *t* test was used primarily to compare the means for survey responses across different sociodemographic groups, while the χ^2 tests assessed contingency table variable correlation. The contingency tables presented here evaluate the correlation between variables to find connections among different groups of respondents.

2.3 Introduction to the Survey and Survey Results

Survey questions included sociodemographic questions, as well as questions focused on wildfire risk, risk perceptions, neighborhood engagement, and preferences for wildfire risk reducing activities. This portion of the survey was designed to take approximately 50% of the total survey time. The questions were designed to keep the cognitive burden low, as to not strain respondents with an extensive survey. The multiple-choice/select style survey questions were grouped into five categories (with Section 5 being reserved for the choice experiment):

Section 1: Questions About Your Home and Property

Section 2: Activities You Take to Reduce Wildfire Risk

Section 3: Land Management Agencies and You

Section 4: Your Neighbors and Their Property

Section 6: Sociodemographic Questions

The two locations for this survey were the Fairbanks North Star Borough (FNSB), as well and the Kenai Peninsula Borough (KPB). Homeowners in these areas where also categorized by their objective wildfire risk as defined by their respective Community Wildfire Protection Plan (CWPP). The National Wildfire Coordinating Group also makes recommendations that were used in the creation of the risk assessment questions in the survey.

While the organization of this chapter will follow that of the survey, there are many overlapping themes to consider when discussing these results. Risk, perceived risk, borough differences, insurance,

[3] Homeowners were selected using the RAND() function in Microsoft Excel.
[4] Only one mail survey was requested and was never returned.

and risk reducing activities will be discussed both as it arises in the survey, and as a more comprehensive topic once the survey can be examined in its entirety.

2.3.1 Questions About Your Home and Property

Maintaining a defensible space around a home is a key component to protecting property from wildfire. This includes keeping flammable fuel sources and unmaintained vegetation away from the building structure, preferably at least 100ft away from the home (National Fire Protection Agency – Firewise 2019). Initial questions in this section detailed the property and home sizes of the respondents, as well as the length of time the respondents have owned their property. One of the more integral questions asked in this section was related to the defensible space around the respondent's home. Defensible space is defined as the area around a home that is free from vegetation, or flammable non-vegetative fuel sources. The Federal Emergency Management Agency (FEMA) recommends homeowners eliminate all combustible materials within at least 30 feet of the home. Table 2.1 outlines the defensible space responses across the entire survey as well as the values for the individual boroughs. Most homes (66.9%) represented in this survey had combustible materials within 30 feet of the main structure. The KPB respondents reported 10% more homes that had combustible materials within 30 feet compared to homes in the FNSB. There is a statistically significant difference between respondents by borough in reported defensible space (χ^2 *p* value = 0.046). When evaluated at mean proportions, FNSB homeowners report more defensible space than KPB homeowners. While this variable can have an interesting interpretation about the state of homes in these boroughs, we can also use this variable to categorize other survey data in order to describe other types of risk reducing behavior.

Table 2.1: Defensible space responses by borough and for all respondents in total. (χ^2 *p* value = 0.046)

Defensible Space	FNSB	KPB	Total
0-10 ft	58 (24.7%)	48 (35.0%)	106 (28.5%)
10-30 ft	91 (38.7%)	52 (38.0%)	143 (38.4%)
30-100 ft	83 (35.3%)	33 (24.1%)	116 (31.2%)
Further than 100ft	3 (1.3%)	4 (2.9%)	7 (1.9%)
Total	235 (100%)	137 (100%)	372 (100%)
Percentage of Homes with flammable material within 30 ft of home	63.40%	72.99%	66.94%

These values change when looking at the risk breakdowns. Table 2.2 shows that the objective wildfire risk zone was also found to be a significant indicator of defensible space (χ^2 *p* value = 0.048). Those in the 'Extreme' fire risk zone tended to keep unmaintained vegetation further away than those in relatively lower risk areas. Table 2.2 also shows the overall sample of respondents who took part in the survey based on their objective wildfire risk.

Table 2.2: Defensible space responses by risk zone and for all respondents in total. (χ^2 p value = 0.048). Also includes counts for objective risk zone by borough.

	High Risk	Very High Risk	Extreme Risk	Total
within 0-10 ft. from home	24 (25.8%)	54 (34.8%)	28 (22.6%)	106 (28.5%)
within 10-30 ft. from home	42 (45.2%)	59 (38.1%)	42 (33.9%)	143 (38.4%)
within 30-100 ft. from home	27 (29%)	38 (24.5%)	51 (41.1%)	116 (31.2%)
further than 100 ft. from home	0 (0%)	4 (2.6%)	3 (2.4%)	7 (1.9%)
Total	93 (100%)	155 (100%)	124 (100%)	372 (100%)
FNSB	99 (100%)	99 (62.7%)	45 (34.4%)	243 (62.6%)
KPB	0 (0%)	59 (37.3%)	86 (65.6%)	145 (37.4%)
Total	99 (100%)	158 (100%)	131 (100%)	388 (100%)

Table 2.3 shows the distribution of housing construction materials by borough. There are three variables created to categorize the construction materials. The "Percentage of people with Wood or Asphalt roofs" was defined to draw attention to homeowners who do not have the optimal roofing material to defend against home ignition due to wildfire. The "Percentage of people with flammable siding" was defined to include homeowners who had either log, timber, or wood siding. Finally, the number of respondents who indicated they had a balcony, deck, or porch made of wood was compared with the total number of respondents for that question to get the "Percentage of respondents that have a balcony, deck, or porch made of wood" value.

Table 2.3: Responses to home construction materials questions broken down by borough. Includes percentages of those falling into created categories.

	FNSB	KPB	Total
Wood (Shake) Shingles	6	4	10
Asphalt Shingles	99	63	162
Metal, Tile, or other Non-combustible roofing	131	73	204
Log or Timber siding	35	32	67
Wood siding	136	78	214
Vinyl siding	30	17	47
Cement, Brick, Stone or other masonry siding	10	11	21
Balcony, Deck, or Porch made of wood	162	104	266
Percentage of people with Wood or Asphalt roofs	44.49%	47.86%	45.74%
Percentage of people with flammable siding	81.04%	79.71%	80.52%
Percentage of respondents that have a balcony, deck, or porch made of wood	68.07%	74.29%	70.37%
Number of Respondents	238	140	378

Based on the information from the table, many of the homes represented in the survey are built with either flammable, or non-optimal material. While only a few respondents indicated that they had wood shingles, many indicated that they had asphalt shingles[5]. Close to 50% of all homes were built from either one of these non-optimal roofing materials. There is only roughly a 3% difference in the number of non-optimal roofs in the FNSB compared to the KPB. The number of homeowners who indicated they had flammable siding was very high. This was due primarily from the large number of people with wood siding. While the specifics of the state of the material were not examined, these homes still represent a non-optimal construction in terms of ignition risk from wildfire. Again, there is only a slight difference in these values due to location (only about 1.3%). Finally, a similarly high number of homeowners indicated that they had a balcony, deck, or porch made of wood.

[5] While asphalt shingles are not inherently a poor choice for minimizing ignition risk due to wildfire, they do have a wide range of flammability. We cannot be assured of their fire resistance or ignition risk minimization based on the construction material alone. This is the justification to classify them as non-optimal for the sake of this analysis.

Table 2.4: Responses to home construction materials questions broken down by wildfire risk. Includes total number of respondents in each wildfire risk zone.

	High	Very high	Extreme	Total
Wood (Shake) Shingles	3	4	3	10
Asphalt Shingles	49	64	49	162
Metal, Tile, or other Non-combustible roofing	46	84	74	204
Log or Timber siding	12	30	25	67
Wood siding	61	83	70	214
Vinyl siding	11	21	15	47
Cement, Brick, Stone or other masonry siding	4	10	7	21
Balcony, Deck, or Porch made of wood	69	110	87	266
Percentage of people with Wood or Asphalt roofs	53.06%	44.74%	41.27%	45.74%
Percentage of people with flammable siding	82.95%	78.47%	81.20%	80.52%
Percentage of respondents that have a balcony, deck, or porch made of wood	70.41%	71.43%	69.05%	70.37%
Number of Respondents	98	154	126	378

Table 2.4 shows the distribution of home construction materials, but with respect to wildfire risk zones. In percentage terms, we observe similar values when comparing the data from table 2.4 to table 2.3. There was little change in these values across risk zones for flammable siding and exterior wooden structures. However, there does seem to be a significant change in roofing material used for homes in the different wildfire risk zones. A little more than half (53.06%) of all homes represented in the survey that were in "High" wildfire risk had non-optimal roofing material. This value drops more than 8% when moving to the "Very High" risk zone (44.74%). It further drops another 3.5% from the "Very High" risk zones to the "Extreme" risk zones (41.27%). In total, there is an 11.8% difference in this value from "High" wildfire risk to "Extreme" wildfire risk. The direction of the change indicates that as the risk increases, the non-optimality of roofing material decreases. While it may be tempting to suggest that this observation is due to homeowners reacting to higher wildfire risk, or more neighborhood information outreach, we should keep in mind that we do not see the same changes in other areas of similarly priced home building construction material (wood siding or wooden decks).

Respondents were asked what the wildfire risk was to their property if a wildfire event occurred in their neighborhood. We see pertinent discrepancies when these responses are compared to the respondent's objective wildfire risk from the CWPP. Table 2.5 shows how respondents identified their own subjective risk in comparison to their objective risk. This is of critical importance, as misidentification of risk may lead to under provision of mitigation actions. Only 29% of respondents in the FNSB properly identified their wildfire risk as "High". Those in extreme risk areas identified their risk slightly better than those in other risk zones. The majority of KNSB respondents labeled their risk as medium or low (71%). The KPB was only slightly better with 33% of respondents properly identifying their risk to wildfire and 67% incorrectly identifying their risk. Those KPB residents in extreme risk zones were again slightly more aware of their own risk to wildfire. However, these small differences were not statistically significant in the aggregate when comparing the mean responses between boroughs (t test p value=0.3). This suggests that the problem of misidentification of risk in endemic to all Alaskan homeowners in high wildfire risk WUI areas.

Table 2.5: Subjective risk vs. objective risk by borough. Responses to the question: "If a wildfire occurred in your neighborhood, how would you rate your property's risk of wildfire?" broken down by objective respondent CWPP risk zone. (FNSB χ^2 p value = 0.71 KPB χ^2 p value = 0.77).

If a wildfire occurred in your neighborhood, how would you rate your property's risk of wildfire? (Subjective risk)	Objective CWPP Risk - High	Objective CWPP Risk – Very high	Objective CWPP Risk - Extreme	Total
FNSB				
high	27 (27.8%)	28 (28.9%)	14 (32.6%)	69 (29.1%)
medium	50 (51.5%)	48 (49.5%)	24 (55.8%)	122 (51.5%)
low	20 (20.6%)	21 (21.6%)	5 (11.6%)	46 (19.4%)
FNSB Totals	97 (100%)	97 (100%)	43 (100%)	237 (100%)
KPB				
high	-	15 (26.3%)	31 (37.8%)	46 (33.1%)
medium	-	28 (49.1%)	42 (51.2%)	70 (50.4%)
low	-	14 (24.6%)	9 (11.0%)	23 (16.5%)
KPB Totals	-	57 (100%)	82 (100%)	139 (100%)

Another measure of risk assessment comes from another question in the survey. Respondents were asked "Which statement best describes your perception of the risk wildfire presents to your home?" Respondents were given choices ranging from "Wildfire will threaten my home in the next 10 years" to "Wildfire will not threaten my home in the next 10 years"[6]. These responses can be organized into two groups: those that believe wildfire will have some effect on their home in the next 10 years, and those that do not. Those that self-identified as not having any idea of their wildfire risk in this context were included in the latter group, as they were not aware of the objective wildfire risk. Given the risk factors in the WUI locations of respondents, most homeowners should acknowledge some risk of wildfire to their homes,

[6] The full range of responses included "will not", "will probably not", "will probably" and "will" as modifiers to the risk assessment.

even in the timespan as short as 10 years. With this assumption, we can again compare those who correctly identify their risk. Table 2.6 shows how those in the FNSB and KPB responded with respect to their wildfire risk zone. Again, we see that most respondents indicated they were at less risk than actual CWPP wildfire risk. Only 46% of FNSB respondents thought that wildfire may threaten their homes in the next 10 years. While there are small changes between the actual risk zones, these changes were shown to not be significant (χ^2 test p value = 0.937). We can see a similar result in the KPB, with a smaller 43% indicating that wildfire may threaten their home in the next 10 years. Again, the results from KPB respondents are not statistically different from the FNSB responses for this question (t test p value=0.513). While these percentages are larger than in the previous table, they still suggest a couple of things. One, a lack of information is a persistent issue for homeowners in these areas, and two, there were no statistical differences between the borough respondents, again indicating a constant issue with a lack of information amongst Alaskan WUI homeowners. These assertions are based on the assumption that all respondents in the sample should expect some threat (non-zero) to their homes over the next 10 years based on their objective CWPP risk.

Table 2.6: Risk perception vs. objective risk by borough. Responses to question "Which statement best describes your perception of the risk wildfire presents to your home?" split by borough and objective wildfire risk. (FNSB χ^2 p value =0.94 KPB χ^2 p value = 0.15).

Which statement best describes your perception of the risk wildfire presents to your home?	High	Very High	Extreme	Total
FNSB				
Will/May threaten	46 (46.9%)	43 (44.8%)	19 (44.2%)	108 (45.6%)
Will/May not threaten	52 (53.1%)	53 (55.2%)	24 (55.8%)	129 (54.4%)
FNSB Total	98 (100.0%)	96 (100.0%)	43 (100.0%)	237 (100.0%)
KPB				
Will/May threaten	-	20 (35.7%)	39 (48.1%)	59 (43.1%)
Will/May not threaten	-	36 (64.3%)	42 (51.9%)	78 (56.9%)
KPB Total	-	56 (100.0%)	81 (100.0%)	137 (100.0%)

Approximately 10% of respondents indicated that they did not purchase homeowner's insurance when asked about their insurance premiums (36 out of 375). These homeowners may not have homeowner's insurance for different reasons, including low home values, the lack of a mortgage payment, or low risk aversion. When compared to respondents who purchased homeowner's insurance, there were no statistically significant changes in risk perception responses. Table 2.7 shows a contingency table for insured and noninsured respondents and risk perception counts. The two questions being compared are the two previous risk perception questions: "Which statement best describes your perception of the risk wildfire presents to your home?" (describe risk) and "If a wildfire occurred in your neighborhood, how would you rate your property's risk of wildfire?" (risk to property) These two questions were statistically equivalent for insured and noninsured homeowners (risk to prop χ^2 *p* value=0.682 and describe risk χ^2 *p* value=0.1887). A *t* test also supports this, which gives *p* values of 0.458 and 0.167 when comparing the mean responses for each question across insured status. This facet of homeowner behavior is notoriously difficult to examine, as lenders often require homeowner's insurance as a contingency of the loan. From this perspective, we can adjust our groups, from insured vs uninsured, to well insured and not well insured. We define a well-insured homeowner as someone who pays over $100 per month, and a not well-insured homeowner as all others. However, doing this also gives us the same result, as seen in table 2.8 (χ^2 and respective *t* test *p* values are both greater than 0.1). For these Alaskan homeowners, responses to this insurance question are not a good indicator of respondent risk perception.

Table 2.7: Insurance vs. risk perception and objective risk. Pair of 2x2 contingency tables showing the effects of insurance to risk perception questions: "describe risk" χ^2 *p* value=0.19 and "risk to property" χ^2 *p* value=0.68.

	describe risk		risk to property	
	Will threaten	Will not threaten	High risk	Not high risk
Insured	130	129	72	187
Not Insured	20	12	10	22

Table 2.8: Well insured vs. risk perception and objective risk. Pair of 2x2 contingency tables showing the effects of insurance to risk perception questions: "describe risk" χ^2 *p* value=0.26 and "risk to property" χ^2 *p* value=0.46.

	describe risk		risk to property	
	Will threaten	Will not threaten	High risk	Not high risk
Well Insured	63	90	43	110
Not Well Insured	104	117	70	151

2.3.2 Activities You Take to Reduce Wildfire Risk – Land Management Agencies and You

The second and third sections of the survey look at what actions homeowners have taken on their property, and how surrounding lands affect their decision making with respect to wildfire risk mitigation. A simple binary choice question opens section 2: "Have you taken any action to reduce wildfire risk to your property?" This question acted as a gate that allowed respondents to explain what type of mitigation actions they have taken or skip to other questions. This provided a small relief from the survey's cognitive burden for any respondent who hadn't participated in any mitigation actions. The descriptive statistics of this and the following questions are shown in tables 2.9, 2.10 and 2.11.

Table 2.9: Mitigation action vs. objective risk and borough. Responses to opening question broken down by fire risk and borough (Borough *t* test *p* values =0.78, Risk zone ANOVA between groups *p* value=0.88).

Have wildfire mitigation activities been done on your home or property?	High Risk	Very High Risk	Extreme Risk	FNSB	KPB	All Risk Levels
Yes	76 (81.7%)	136 (81.2%)	103 (81.8%)	200 (84.4%)	115 (83.3%)	315 (84.0%)
No	17 (18.3%)	20 (12.8%)	23 (18.2%)	37 (15.6%)	23 (16.7%)	60 (16.0%)
TOTAL:	93 (100%)	156 (100%)	126 (100%)	237 (100%)	138 (100%)	375 (100%)

Much of these specific mitigation actions showed no statistical difference when comparing groups. There was no discernable difference in the way homeowners in different boroughs chose mitigation actions (*t* test *p* values =0.78). This suggests that homeowners in these two boroughs participate in mitigation actions in a similar way. This is yet another example of there being no statistical difference in the way these two boroughs approach some aspect of wildfire mitigation. Table 2.12 shows that this was not the case when it comes to differences in wildfire risk areas. Four risk mitigation actions had differences amongst homeowner wildfire risk area. Regularly clearing leaves for risk reduction and appearance purposes showed significant differences in extreme and non-extreme risk zones, and High and non-high-risk zones respectively. Specifically, homeowners in extreme wildfire risk zones were less likely to clear leaves from their roofs for wildfire risk reduction than those in any other risk area. Home ignition probabilities may be increased when there are more flammable fuels on roofs, so this lack of action seems to be particularly alarming in an extreme risk area. Borough did not factor into this, as we compared objective risk areas only. This indicates that Alaskan homeowners in extreme risk areas are partaking in this activity less when compared to those in high, or very high areas. Those in high risk areas were more likely to clear leaves from their roofs for appearances, but less likely to keep the first 100 feet around the home cleared. Finally, those in extreme risk areas mowed tall grasses more often on their property for appearances when compared to those in very high-risk zones.

Table 2.10: Frequency counts of mitigation actions taken by objective wildfire risk zones. Percentages are proportion of those who took that action from all those mitigate, and all respondents respectively.

	High Risk	Very High Risk	Extreme Risk	All Respondents
installed fire resistant siding	6 (7.89%, 6.06%)	12 (8.82%, 7.59%)	8 (7.77%, 6.11%)	26 (8.25%, 6.93%)
installed fire resistant roofing	25 (32.89%, 25.25%)	50 (36.76%, 31.65%)	45 (43.69%, 34.35%)	120 (38.1%, 32%)
installed screening over roof vents	10 (13.16%, 10.1%)	18 (13.24%, 11.39%)	16 (15.53%, 12.21%)	44 (13.97%, 11.73%)
installed a chimney spark arrester	9 (11.84%, 9.09%)	24 (17.65%, 15.19%)	16 (15.53%, 12.21%)	49 (15.56%, 13.07%)
widened the road leading to property	19 (25%, 19.19%)	37 (27.21%, 23.42%)	27 (26.21%, 20.61%)	83 (26.35%, 22.13%)
regularly cleared leaves from roof to reduce wildfire risk	35 (46.05%, 35.35%)	62 (45.59%, 39.24%)	25 (24.27%, 19.08%)	122 (38.73%, 32.53%)
regularly cleared leaves from roof for appearance purposes	25 (32.89%, 25.25%)	28 (20.59%, 17.72%)	17 (16.5%, 12.98%)	70 (22.22%, 18.67%)
regularly cleared first 10 feet of land around your home of light brush	49 (64.47%, 49.49%)	82 (60.29%, 51.9%)	62 (60.19%, 47.33%)	193 (61.27%, 51.47%)
regularly cleared first 50 feet of land around your home of light brush	35 (46.05%, 35.35%)	71 (52.21%, 44.94%)	46 (44.66%, 35.11%)	152 (48.25%, 40.53%)
regularly cleared first 100 feet of land around your home of light brush	7 (9.21%, 7.07%)	29 (21.32%, 18.35%)	23 (22.33%, 17.56%)	59 (18.73%, 15.73%)
regularly cleared leaves from yard for appearance purposes	35 (46.05%, 35.35%)	52 (38.24%, 32.91%)	42 (40.78%, 32.06%)	129 (40.95%, 34.4%)
pruned and trimmed trees and bushes	59 (77.63%, 59.6%)	96 (70.59%, 60.76%)	72 (69.9%, 54.96%)	227 (72.06%, 60.53%)
cut down dead or decaying trees	62 (81.58%, 62.63%)	118 (86.76%, 74.68%)	89 (86.41%, 67.94%)	269 (85.4%, 71.73%)
thinned dense areas of vegetation	50 (65.79%, 50.51%)	81 (59.56%, 51.27%)	56 (54.37%, 42.75%)	187 (59.37%, 49.87%)
mowed long grasses to reduce wildfire risk	32 (42.11%, 32.32%)	71 (52.21%, 44.94%)	55 (53.4%, 41.98%)	158 (50.16%, 42.13%)
mowed long grasses for appearance purposes	41 (53.95%, 41.41%)	63 (46.32%, 39.87%)	62 (60.19%, 47.33%)	166 (52.7%, 44.27%)
other: [Respondent Specify]	10 (13.16%, 10.1%)	16 (11.76%, 10.13%)	14 (13.59%, 10.69%)	40 (12.7%, 10.67%)
N (answered yes to mitigation question)	76	136	103	315
N (all respondents)	99	158	131	388

Table 2.11: Frequency counts of mitigation actions taken by borough. Percentages are proportion of those who took that action from all those mitigate, and all respondents respectively.

	FNSB	KPB	All Respondents
installed fire resistant siding	14 (7%, 5.76%)	12 (10.43%, 8.28%)	26 (8.25%, 6.93%)
installed fire resistant roofing	78 (39%, 32.1%)	42 (36.52%, 28.97%)	120 (38.1%, 32%)
installed screening over roof vents	26 (13%, 10.7%)	18 (15.65%, 12.41%)	44 (13.97%, 11.73%)
installed a chimney spark arrester	27 (13.5%, 11.11%)	22 (19.13%, 15.17%)	49 (15.56%, 13.07%)
widened the road leading to property	51 (25.5%, 20.99%)	32 (27.83%, 22.07%)	83 (26.35%, 22.13%)
regularly cleared leaves from roof to reduce wildfire risk	78 (39%, 32.1%)	44 (38.26%, 30.34%)	122 (38.73%, 32.53%)
regularly cleared leaves from roof for appearance purposes	44 (22%, 18.11%)	26 (22.61%, 17.93%)	70 (22.22%, 18.67%)
regularly cleared first 10 feet of land around your home of light brush	119 (59.5%, 48.97%)	74 (64.35%, 51.03%)	193 (61.27%, 51.47%)
regularly cleared first 50 feet of land around your home of light brush	92 (46%, 37.86%)	60 (52.17%, 41.38%)	152 (48.25%, 40.53%)
regularly cleared first 100 feet of land around your home of light brush	38 (19%, 15.64%)	21 (18.26%, 14.48%)	59 (18.73%, 15.73%)
regularly cleared leaves from yard for appearance purposes	80 (40%, 32.92%)	49 (42.61%, 33.79%)	129 (40.95%, 34.4%)
pruned and trimmed trees and bushes	148 (74%, 60.91%)	79 (68.7%, 54.48%)	227 (72.06%, 60.53%)
cut down dead or decaying trees	166 (83%, 68.31%)	103 (89.57%, 71.03%)	269 (85.4%, 71.73%)
thinned dense areas of vegetation	121 (60.5%, 49.79%)	66 (57.39%, 45.52%)	187 (59.37%, 49.87%)
mowed long grasses to reduce wildfire risk	101 (50.5%, 41.56%)	57 (49.57%, 39.31%)	158 (50.16%, 42.13%)
mowed long grasses for appearance purposes	105 (52.5%, 43.21%)	61 (53.04%, 42.07%)	166 (52.7%, 44.27%)
other: [Respondent Specify]	24 (12%, 9.88%)	16 (13.91%, 11.03%)	40 (12.7%, 10.67%)
N (answered yes to mitigation question)	200	115	315
N (all respondents)	243	145	388

Table 2.12: Mitigation action p value testing by objective risk and borough. p values for two tailed t tests comparing means for specified mitigation actions across objective wildfire risk and borough. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

t test	High vs Very High	High vs Extreme	Very High vs Extreme	FNSB vs KPB
installed fire resistant siding	0.817	0.975	0.771	0.288
installed fire resistant roofing	0.574	0.145	0.281	0.664
installed screening over roof vents	0.987	0.658	0.616	0.515
installed a chimney spark arrester	0.266	0.484	0.666	0.185
widened the road leading to property	0.728	0.855	0.864	0.653
regularly cleared leaves from roof to reduce wildfire risk	0.948	0.002***	0.001***	0.897
regularly cleared leaves from roof for appearance purposes	0.047**	0.01***	0.426	0.901
regularly cleared first 10 feet of land around your home of light brush	0.55	0.562	0.988	0.397
regularly cleared first 50 feet of land around your home of light brush	0.393	0.854	0.25	0.293
regularly cleared first 100 feet of land around your home of light brush	0.024**	0.02**	0.853	0.872
regularly cleared leaves from yard for appearance purposes	0.269	0.484	0.692	0.652
pruned and trimmed trees and bushes	0.269	0.251	0.909	0.314
cut down dead or decaying trees	0.314	0.382	0.936	0.113
thinned dense areas of vegetation	0.373	0.126	0.424	0.59
mowed long grasses to reduce wildfire risk	0.16	0.137	0.856	0.874
mowed long grasses for appearance purposes	0.289	0.406	0.034**	0.926
other: [Respondent Specify]	0.768	0.933	0.674	0.625

Respondents were asked what would discourage them from taking additional steps to reduce their wildfire risk. They were given the following responses and could select as many choices as applied. The selection choices and descriptive statistics are shown in table 2.13. Loss of privacy was the most selected reason (62% of all respondents) to not take any risk reduction action across all respondents.

Table 2.13: Disincentives to taking risk reducing actions. Responses to question regarding what would discourage a homeowner from undertaking risk mitigating actions.

What would discourage you from taking risk reduction actions?	Count	Sum	% selected
Changing Landscape	375	51	13.6%
Losing Privacy	375	236	62.9%
Changing Views	375	63	16.8%
Losing Shade or Windbreaks	375	108	28.8%
Only Mitigation Participant	375	31	8.3%

Respondents were then asked about potential incentives to encourage risk reduction actions. This allowed respondents to indicate their inducements, instead of deterrents as was asked in the previous question. We also included a follow-up question, which only focused on LMA actions on nearby public lands. The possible answer choices and descriptive statistics are included in table 2.14.

Table 2.14: Responses to question regarding fuel reduction preferences. Responses to the first question were multiple select and respondents could choose as many as applied. LMA preference question was multiple choice.

Which Method of LMA fuel reduction would you prefer?	Count	Sum	% selected	
Cleared public lands	373	85	22.8%	
Shaded public lands	373	73	19.6%	
Neighbors also reducing fuels	373	183	49.1%	
neighborhood involvement (Firewise)	373	174	46.6%	
Risk mitigation action subsidies	373	195	52.3%	
Homeowners insurance premium discount	373	282	75.6%	
Property tax discount	373	282	75.6%	
	Count	Cleared	Thinned	None
LMA Preference	346	38 (11.0%)	277 (80.1%)	31 (9.0%)

For illustrative purposes, we can group these choices into three categories: LMA action (cleared and shaded public lands), neighborhood involvement (also includes neighbors reducing fuels), and direct payment (subsidies and discounts). The first group had the lowest response, with no significant difference between cleared and shaded public lands. This directly contradicts the responses from the follow-up question, where homeowners had a very clear preference for thinned fuel breaks. While it may be difficult to directly compare these two questions, we can draw a few conclusions from this difference. The first is that the follow-up question included graphic depictions of the fuel break, including what an untreated tract of land would look like. This is more informative than the text responses in the previous question. It also may indicate an information gap in terminology, as a shaded fuel treatment and a thinned fuel treatment are virtually synonymous. Finally, this discrepancy may not be a discrepancy at all if neighborhood involvement and direct payments are just much more preferred to LMA action. It is possible that for those who choose LMA actions, thinning is preferred over other options. The neighborhood involvement was preferred by almost half of all respondents, with no significant differences between specific options. Lastly, direct payment options were most preferred, with 52%-75% of respondents selecting one of these options. Within this group, discount to premiums and property taxes were significantly different from mitigation subsidies (t test p value <0.01 for both). Based on these responses, people preferred direct payments, neighborhood participation, and LMA action in that order. While any individual incentive may not be feasible, understanding these preferences may allow decision makers to appropriately make cost effective decisions when attempting to increase participation in community wide wildfire risk reduction.

2.3.3 Neighbors and their Property – Survey Respondent Demographics

The fourth and sixth sections of the survey covered neighborhood participation and sociodemographic questions respectively. These questions centered around the behavior of other neighborhood homeowners and their participation in risk mitigation activities. Respondents were asked about their closest neighbors' defensible space around their house. The answer choices were identical to those in section two, which asked about the homeowners own defensible space. Table 2.15 shows the results of this question split by borough. There was no statistical significance between boroughs from the defensible space that neighbors had around their property, with most neighbors clearing somewhere between 10-100 feet around their home (χ^2 test p value < 0.66). Own defensible space was different between boroughs, while neighbor defensible space was not. This may seem to create of a contradiction, but respondents are assumed to have a random neighbor that does not correspond to their own mitigation actions. When viewed in the context of respondent self-selection, this difference may indicate that respondents in the FNSB were more inclined to keep larger defensible space than those in the KPB[7].

Table 2.15: Neighbor defensible space by borough. Closest neighbor defensible space responses broken down by borough and for all respondents in total.

Defensible Space	FNSB	KPB	Total
0-10	31 (12.8%)	22 (15.2%)	53 (13.7%)
10-30	67 (27.6%)	35 (24.1%)	102 (26.3%)
30-100	85 (35%)	40 (27.6%)	125 (32.2%)
100+	31 (12.8%)	18 (12.4%)	49 (12.6%)
Total	243 (100%)	145 (100%)	388 (100%)

Free riding behavior was examined in the context of this defensible space question. The neighbors' defensible space responses were compared to the respondents own defensible space question. Table 2.16 shows the contingency table for respondents in the FNSB and the KPB. Both boroughs had significant differences between their own defensible space, and the defensible space of their closest neighbor. However, it seems that the most respondents at least matched the level of their neighbor's defensible space. This suggests that free riding communal risk reductions from defensible space was not commonplace in either borough. This may indicate a level of shared defensible space participation within a neighborhood. Other alternatives are presented in section 2.4.4.

[7] Or conversely, KPB respondents who participated in the survey may have been less likely to keep larger defensible space.

Table 2.16: Own defensible space vs. neighbor defensible space by borough. Two contingency tables examining the frequency of own defensible space and the closest neighbor's defensible space. Both tables show statistical significance (FNSB χ^2 test p value = 0.03 and KPB χ^2 test p value < 0.01).

	Own Defensible Space				
Neighbor's Defensible Space-FNSB	0-10	10-30	30-100	100+	Total
0-10	14 (26.4%)	8 (9.9%)	7 (9.5%)	1 (33.3%)	30
10-30	19 (35.8%)	31 (38.3%)	16 (21.6%)	0 (0%)	66
30-100	15 (28.3%)	29 (35.8%)	39 (52.7%)	2 (66.6%)	85
100+	5 (9.4%)	13 (16.0%)	12 (16.2%)	0 (0%)	30
Neighbor's Defensible Space-KPB					
0-10	15 (36.6%)	5 (11.6%)	1 (3.8%)	0 (0%)	21
10-30	12 (29.3%)	19 (44.2%)	3 (11.5%)	1 (33.3%)	35
30-100	11 (26.8%)	15 (34.9%)	13 (50.0%)	0 (0%)	39
100+	3 (7.3%)	4 (9.3%)	9 (34.6%)	2 (66.6%)	18

Sociodemographic indicators are shown in table 2.17. The median age for the population of Alaska was 33.5 in 2017. When comparing this to our survey sample demographics, we see that there is an upward shift in the age of our respondents. Only 35% of survey respondents were under the age of 50. This conflicts with data from the national Association of REALTORS which shows that nationally 62% of home buyers were younger than 52 (National Association of REALTORS Research Department 2018). This upward shift in age may influence other sociodemographic indicators, like income and education. Ethnicity responses weren't very illustrative, since 74% or respondents indicated that they were white. While this on its own can still be illustrative, the only other comparative group would be the amalgamation of all other ethnicities. This 'minority' group would only comprise 4% or all respondents. Not only does this create its own inferencing trouble for associating responses with larger populations, it presumes homogeneity amongst those in that group. Many of the "other" responses included comments indicating the reluctance of homeowners to provide ethnicity information in this format, further compounding these analysis issues. Males were more likely to respond, with 62% of homeowners surveyed being male. This is different from general Alaskan demographics, with males making up 52.1% of the population. While approximately half of all Alaskans are married, 70% of those who gave marital status information were married. Education levels were also skewed upwards. 71% of the Alaskan population has not received a bachelor's degree, while only 42.6% or our sample was in the same group. In general, our survey respondents were more likely to be older married males with higher education degrees and higher incomes. Table 2.18 shows the sociodemographic makeup of our sample and how it differs from state and national benchmarks. Again, the largest discrepancies are in education, age, and income.

Table 2.17: Table of sample demographics of all survey respondents. Categories include age, ethnicity, gender, marital status, income, employment, education and household size.

Age	#
20-30	7
30-40	47
40-50	62
50-60	86
60-70	95
70-80	33
80-90	4
(blank)	54
Grand Total	388

Ethnicity	#
White	287
Black	0
Alaskan Native	10
Asian	3
Pacific Islander	0
Latino	3
Two or more	11
Other	12
(blank)	62
Grand Total	388

Gender	#
Male	207
Female	127
(blank)	54
Grand Total	388

Marital Status	#
single	54
married	235
divorced	30
separated	1
widowed	14
(blank)	54
Grand Total	388

Income	#
less than 10k	5
10k-20k	12
20k-30k	12
30k-40k	12
40k-50k	13
50k-60k	25
60k-70k	24
70k-80k	36
80k-90k	29
90k-100k	27
100k-110k	27
110k-120k	12
120k-130k	17
130k-140k	20
140k-150k	11
150k+	40
(blank)	66
Grand Total	388

Employment Status	#
unemployed	17
self employed	44
part time 20 less	12
part time 20-39	21
full time	160
retired	80
(blank)	54
Grand Total	388

Education	#
No High school Diploma	4
High School Diploma	22
Some college	63
Associate degree	35
Professional certification	18
Bachelor's degree	107
Graduate degree	63
Doctorate/PhD	21
(blank)	55
Grand Total	388

People in Household	#
1	62
2	149
3	51
4	44
5	15
6	5
6 or more	5
(blank)	57
Grand Total	388

Table 2.18. Comparison of survey sociodemographic breakdown. Compares survey values with the state of Alaska and the US. Values are percentages to total population. Alaska and US values come from the US Census 2017 ACS Survey (US Census 2019).

Education	Survey	Alaska	US
Less than High school	1.2%	7.6%	12.7%
High School Graduate W/O Bachelor's degree	41.4%	63.4%	56.4%
Bachelor's degree or higher	57.4%	29.0%	30.9%
Gender			
Male	62.0%	52.1%	49.2%
Female	38.0%	47.9%	50.8%
Age			
Less than 20	0.0%	27.6%	25.7%
20-30	2.1%	16.3%	14.0%
30-40	14.1%	14.2%	13.1%
40-50	18.6%	12.1%	12.8%
50-60	25.7%	13.8%	13.6%
60-70	28.4%	10.0%	11.0%
70-80	9.9%	4.1%	6.2%
80+	1.2%	1.7%	3.7%
Annual Household Income			
Less than $50k	16.77%	31.40%	43.90%
$50k-$100k	43.79%	32.40%	30.00%
$100k-$150k	27.02%	19.70%	14.10%
More than $150k	12.42%	16.50%	12.10%

Income information was collected from respondents in both boroughs. Since some risk mitigation actions can be costly, income could affect homeowner risk mitigation behavior. Income questions were asked categorically. With the use of household composition information, we created a variable that shows per capita household income. Table 2.19 shows contingency tables comparing income per household member, defensible space and taking any mitigation actions. In terms of defensible space, there was no significant differences in the way income affected a homeowner's defensible space (χ^2 test p value = 0.94). While at first glance this may seem to indicate no differences in actions from income, we should again point out that our sample was skewed in terms of income. Alaska's per capita income in 2017 was $34,222. There were 138 people who were below this threshold, but 193 above it. This means that higher income homeowners were more represented in this sample and may be affecting these results. Mitigation actions were similarly not affected by income (χ^2 test p value = 0.97). Again, we need to acknowledge the role weighting plays into the income analysis.

Table 2.19: Household income by defensible space and mitigation action. Contingency table of income, defensible space and whether the respondent took action.

	Household income (per person)				
Defensible space	2.5k-15k	15k-30k	30k-45k	45k and up	Total
0-10ft	10 (38.5%)	22 (25.3%)	21 (28.4%)	37 (28.7%)	90 (28.5%)
10-30ft	10 (38.5%)	38 (43.7%)	26 (35.1%)	49 (38%)	123 (38.9%)
30-100ft	6 (23.1%)	27 (31%)	25 (33.8%)	40 (31%)	98 (31%)
100ft or more	0 (0%)	0 (0%)	2 (2.7%)	3 (2.3%)	5 (1.6%)
Total	26 (100%)	87 (100%)	74 (100%)	129 (100%)	316 (100%)
	Household income (per person)				
Take mitigation actions?	2.5k-15k	15k-30k	30k-45k	45k and up	Total
Yes	23 (88.5%)	76 (84.4%)	63 (84%)	109 (84.5%)	271 (84.7%)
No	3 (11.5%)	14 (15.6%)	12 (16%)	20 (15.5%)	49 (15.3%)
Total	26 (100%)	90 (100%)	75 (100%)	129 (100%)	320 (100%)

2.4 Discussion

2.4.1 Differences in Borough Responses

The differences between borough homeowner actions were varied. Defensible space around the home was one of the only significant differences between borough respondents. While FNSB residents were more likely to have larger defensible spaces, there were no other notable differences between boroughs. Both boroughs had similar issues with risk perception and had no difference in the specific actions they took. Neither borough showed evidence of free riding behavior, but both showed that neighbors' defensible space was correlated with their own. This indicates that in general, these WUI communities are similar to each other, but may also be representative of Alaskan WUI homeowners in general. The lack of differences between borough responses shows that the underlying population of homeowners in higher risk WUI locations may be the driving force behind responses. Differences between risk zones were similar to the differences between borough. Defensible space seems again to be dependent on homeowner risk zone, as those in extreme risk zones were more likely to clear more space around their house. Risk perception again seems to not be affected by objective risk zone and is linked toward homeowners in higher risk WUI locations in general. There were also slight differences in the way homeowners participated in risk reduction activities. These weren't very significant but did show that there may be some variances between the groups.

2.4.2 Mitigation Actions and Defensible Space

As previously shown in Table 2.9, wildfire risk mitigation actions were done by 84% of all respondents. While the actions were defined very broadly, this on its own would show that homeowners are aware of their objective wildfire risk, supporting the idea of proper self-identification of that risk.

Table 2.2 also showed that there was a correlation between those in higher objective wildfire risk areas and those who kept a larger defensible space. This again indicates that homeowners are at least somewhat aware of general risk, or at least aware of differences in risk areas. However, when compared to actual defensible space responses, we can see drastic differences. Table 2.1 showed that almost 67% of survey respondents kept flammable fuels within 30 feet of their property. Table 2.10 also shows that only 32% of respondents regularly cleared leaves from their roofs, which is a low cost but highly effective tool to reduce ignition risk in the immediate zone (0-5 feet around the house) (National Fire Protection Agency - Firewise 2019). Given these reasons, the risk mitigation actions and defensible space/objective risk correlation may have an alternative explanation. If homeowners are working under the assumption that their activities are sufficient for their subjective risk area, then they can simultaneously take lots of action in general, recognize the need for more actions in higher objective risk zones, and still not be taking enough risk mitigation action. This can be seen both in the misidentification of risk (table 2.5) and the previously mentioned misalignment to standard Firewise compliance (National Fire Protection Agency - Firewise 2019). The negative correlation between living in the extreme objective wildfire risk zone and clearing your roof of leaves furthers this argument, as those homeowners should be most likely to take that mitigation action. The reduction of tree deaths from spruce bark beetles may have even more of an effect on those KPB respondents, furthering the perception of low wildfire risk.

The loss of the amenity value of natural landscapes may also explain some of this under provision of risk mitigation activity. If we assume that these respondents are underproviding risk reducing actions but are fully informed of their objective wildfire risk, they may be acting based on the total utility gained from that choice. Put differently, the individual benefit of reducing one's wildfire risk from reducing flammable fuels is not larger than lost benefit from losing the amenities provided by those fuels. Table 2.13 highlights some evidence for this, as most respondents (62.9%) would be disincentivized to mitigate their wildfire risk if it also meant a loss of privacy. This is also supported by the fact that when asked directly, 84.0% of respondents would prefer land management agencies mechanically thin vegetation over a clear cutting (8.0%) or no action (8.0%). This shows a "best of both worlds" scenario where homeowners could take advantage of lowered risk while simultaneously keep much of the amenity values of the vegetation in the community. Also recall that the two risk reducing activities respondents most engaged in were pruning and/or trimming trees and/or bushes (60.5%) as well as cutting down dead or decaying trees (71.7%). This opens the possibility that homeowners have already taken all the risk reducing actions on their property they want while continuing to maximize their individual utility. This would then indicate a mismatch of incentives between individual homeowners, individual WUI communities, and the land management agencies suppressing and pre-suppressing wildfire.

2.4.3 Policy Implications

In Alaskan WUI areas, the policy implications of the survey responses should be seen in three different ways. The first is under the presumption of cost effectiveness of public spending. For example, shaded fuel treatments were the preferred type of treatment on publicly owned lands, but they may be twice as costly as cleared fuel breaks. Fuel breaks need to be examined in the framework of cost per acre to implement, and amount saved from assumed reductions to economic loss from wildfires (Agee 2000). Furthermore, the costs of thinned fuel treatments can be as much a $8,000[8] per acre in Alaska (St. Clair 2006). If cost effectiveness is not met when implementing the preferred mitigation strategy on public lands, homeowner preferences may be balanced by a payment mechanism to offset costs. This would require estimates for willingness-to-pay, and a broad understanding of covariates affecting these preferences. While a direct method of payment was most preferred, this is likely the least cost-effective method of risk reduction and would require further analysis of homeowner willingness-to-accept. The second policy implication is the benefit of neighborhood participation and information sharing. The hazard literature is consistent when discussing the benefits that education programs and social interaction give in risk management (Paton et al. 2008, Pearce 2003, Cutter et al. 2008). A focus on these types of benefits may provide a relatively cost-effective means to reduce community level wildfire risk by incentivizing mitigation actions. Risk perception issues were common in both study areas, so communication between Alaskan boroughs with high wildfire risk may be beneficial to all Alaskan WUI communities. Leveraging a community's built in resilience to risk mitigation may not only be the preferred method but be much less costly than mechanical thinning of public lands. The third and last way to approach this would be to remember the spatial context of wildfire risk mitigation actions. There was anecdotal evidence that losing shade and the dangers of thawing permafrost was a key factor in risk mitigation decision making. This was seen directly in question responses (Table 2.13), as was the potential of lost amenity values of privacy giving landscape. When planning community wide projects to reduce wildfire risk, keep in mind the complex decision making that individual homeowners perform as well as their wide-ranging spatial preferences. Future research should include follow-up surveys to test longitudinal changes associated with taking risk mitigation actions. Because dichotomous choice questions were asked, logit models can be utilized to estimate the factors that affect the probability of action. This sort of analysis should take care to not omit critical variables, as this sort of bias could lead to incorrect interpretation.

[8] In 2019 dollars

2.4.4 Sources of Bias

There are a few potential sources of bias based on the sample of survey respondents. The first to consider is participation bias based on our response rate. Approximately one in five Alaskan residents sampled participated in the survey. Because of this, we cannot assume that the remaining residents that did not participate would answer similarly to those who chose to participate. If non respondents are thought to be fundamentally different in the context of wildfire risk, this could lead to bias in the results presented. The shifts in sociodemographic variables may also bias our results, if we assume that those groups answer questions differently based on their group alone. For example, those with higher incomes may be able to clear a larger defensible space than those with lower incomes. While a small number of tests showed that there was little difference in the way different sociodemographic groups[9] answered certain questions, this sort of analysis would have to be question and sociodemographic group specific. As mentioned, preliminary testing did not show that this was systematically present across responses and within sociodemographic groups. Social desirability bias may also influence the responses received. The survey presented the concepts of Firewise compliance and defensible space as positive and contributing to community risk reduction. If a respondent felt compelled to answer questions in a way that makes them be viewed in a more positive light, this would lead to upward bias in these types of questions. The free riding conclusions drawn from the defensible space questions may be especially vulnerable to this type of bias, as homeowners may be reluctant to admit a neighbor having more defensible space than them. The fundamental argument for this type of bias would be the ubiquity of Firewise compliance and defensible space as socially positive, which may not actually be the case.

2.5 Conclusion

Both Alaskan boroughs surveyed were seen to respond in very similar ways, with the notable exception being defensible space. Even across objective wildfire risk, there were trends within responses. There was evidence of individual misidentification of objective wildfire risk, as well as under-provision of actions taken based on self-identified neighborhood wildfire risk. This confirms much of the previous literature of WUI communities in the contiguous United States. Informational campaigns on the aggregate effects of community wide risk reduction activities by homeowners may increase participation rates. For those homeowners that were fully informed, amenity values were a significant factor in individual decision making. The loss of privacy and shade were among the most important benefits of not reducing fuels. While there was a significant amount of some mitigation actions being taken, it wasn't at the level necessary for risk reduction commensurate with objective risk. Proper defensible space was lacking, as

[9] Specifically, gender and education level.

were actions taken in the closest zone to the home, such as the removal of vegetation from roofs and the installation of nonflammable house siding. The most preferred direct incentive for increased participation in risk reducing activities were in the form of direct payments (subsidies, discounts etc.). Adaptive capacity building in the form of community wide participation and involvement was also preferred. Finally, there was little evidence of free-riding behavior based on the community wide defensible space self-assessments done by respondents. Future research should include a longitudinal component for follow-ups. When mixed with external factors, they can provide insight into how preferences have changed over time. For example, the 2019 Shovel Creek fire north west of Fairbanks forced evacuations in an area we previously surveyed. Subsequent surveys should focus on this community, as the recent exposure will presumably shift their preferences.

Alaskan WUI communities are vulnerable. Like many other wildfire prone regions, they often balance the comfort and beauty of living in semi-open wildlands with the increased risk from probabilistic wildfire events. There are many options available to WUI homeowners to reduce both home ignition risk, and the probability their property will ignite when a wildfire approaches. However, many variables ultimately determine the observable homeowner action (or inaction) and are governed by multifaceted preferences and constraints. Examining the human dimensions of wildfire risk is crucial for those attempting to increase neighborhood resilience to these hazards. Public agencies can use this information to make the most informed and cost-effective means to achieve neighborhood risk goals in high risk WUI communities. As with many other hazards, we must fully understand the threat before we can appropriately fight against it.

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Chapter 3 Homeowner Preferences of Wildfire Risk Mitigation in the Alaskan Wildland Urban Interface - Choice Experiment Results[1]

Abstract

Naturally occurring wildfire has become a larger threat to human life and property with the proliferation of homes into the wildland urban interface. The state of Alaska has a unique challenge in that wildland urban interface communities are abundant and close to large expanses of dense flammable fuels. The removal of these fuels, both on private and public lands has been shown to reduce wildfire risk in these locations. However, incentivizing private land mitigation is potentially problematic. Homeowner preferences for wildfire risk mitigation in the wildland urban interface is explored via discreet choice experiment to better understand the drivers of their risk mitigation actions. Hierarchical Bayesian analysis provides willingness-to-pay estimates of mitigation cost, public land treatments, neighbor actions and total risk reduction. Willingness-to-pay estimates for wildfire risk reduction were large (>$1000) for all respondents. Even larger willingness-to-pay estimates were seen in respondents who self-identified as subjectively being a high risk for wildfire, as well as significantly lower willingness-to-pay for respondents who self-identified as having subjectively lower wildfire risk. Willingness-to-pay estimates also showed a homeowner preference for thinned, or shaded fuel treatments on public lands, preferring them to cleared treatments. These cleared fuel treatments were least preferred, even less so than having no public land fuel treatment. Future research questions should include a look into the preference of shaded fuel breaks as a reflection of amenity values or of the protection of Alaskan permafrost.

3.1 Introduction

The Wildland Urban Interface (WUI) has been the focus of many studies examining the effects of wildfire on residents and the general economic losses of homeowner property and communities (Holmes et al. 2009, Hammer et al. 2009, Stein et al. 2013). WUI areas are particularly vulnerable to wildfire, since they are directly adjacent to open wildlands. Probabilistic fire events occurring in open wildlands close to WUI communities may give residents very little time to react. Individuals in these communities only have direct control over the fuels on their own property, and not external activities that reduce wildfire ignition and spread outside of their property lines. Even so, homeowners can still make decisions that affect wildfire risk in their neighborhood, and house ignition probabilities from within their own

[1] This chapter is currently being prepared externally for academic journal publication. Other authors on that manuscript include Joseph Little (University of Alaska Fairbanks), Stacy Drury (USDA - US Forest Service), Randi Jandt (University of Alaska Fairbanks) and Brock Lane (University of Alaska Fairbanks).

property lines. It has been shown that the effort put into pre-suppression tactics mitigates the impacts from wildfire spread, and therefore overall suppression costs (Lankoande and Yoder 2006). Because these risk mitigation activities are an important component to suppressing wildfire in WUI communities, programs such as Firewise (National Fire Protection Agency - Firewise 2019) help build community resilience to wildfire via education and the building of social support networks. Since wildfire suppression agents rely so much on the pre-suppression activities of individual private homeowners, our interests lie in understanding the motivations of these homeowners to take part in their own risk mitigation activities. We used a discreet choice experiment (DCE) to estimate an Alaskan homeowner's Willingness-To-Pay (WTP) for general wildfire risk reduction both on their own property and surrounding public lands.

3.1.1 Alaskan Perspective on Wildfire

The state of Alaska must deal with wildfire in a unique way. The size of the state combined with the low population densities make wildfire suppression decisions different than in other areas of the country. Large, thousand-acre fires are sometimes left to burn while only being monitored, since they pose no threat to human safety or significant economic loss (Alaska Department of Natural Resources: Division of Forestry 2019). The low population densities also create large WUI areas across the state. Many Alaskans in these WUI locations are at significantly higher risk than those in more densely populated areas. Mitigation activities done on private lands can provide benefits both to individual homeowners, and to entire WUI communities in the form of shared risk reduction. Addressing wildfire risk is an important policy issue, as land management agencies have been slow to respond to the changing climate and ecology in WUI locations (Dombeck et al. 2004). If state and federal agencies are to find ways to properly incentivize homeowners to reduce fuels on their own property, they must understand how homeowners value this wildfire risk reduction. Specifically, they need to identify the value homeowners place on their own mitigation actions, the level of aggregate neighborhood mitigation activity, and the level of land management agency (LMA) participation. These values could then create the primer for future discussion of wildfire mitigation incentivization programs.

Alaska depends on defining zones to trigger wildfire suppression response. They group all areas of the state into four suppression response zones (Alaska Department of Natural Resources: Division of Forestry 2019). Critical protection zones necessitate immediate suppression and usually are close to larger urban areas, placing people and property in direct and imminent danger. Full protection areas may still require a strong response, though the risk to human life is reduced. Modified protection areas do not require the same level of response as full protection, with the limited zone triggering the least suppression response. From 2007-2015, there have been approximately 173 wildfires that were larger than 50 acres in critical and full protection zones threatening 4733 structures and burning down 169. Most of this structural threat came from three fires, the Caribou Hills fire in 2007, the Hastings fire in 2011 and the Sockeye fire in 2015. In 2015 there were over 5.1 million acres burned in the state, causing widespread smoke and poor visibility for almost all Alaskan residents. From a cost perspective, the Funny River fire in 2014 had a suppression cost of approximately \$11.5 million dollars. The Hastings and Sockeye fires also had high[2] suppression costs of approximately \$18.5 million and \$8 million respectively. The Shovel Creek fire in 2019 had a preliminary cost estimated over \$25 million dollars. The costs associated with wildfire suppression will continue to rise in the face of warming temperatures and WUI proliferation. Estimates of future suppression costs are expected to be over one billion dollars over the next century, averaging \$60 million per year (Melvin et al. 2017). Figure 3.1 shows the spatial distribution of all wildfire ignition points in the state from 2007-2015.

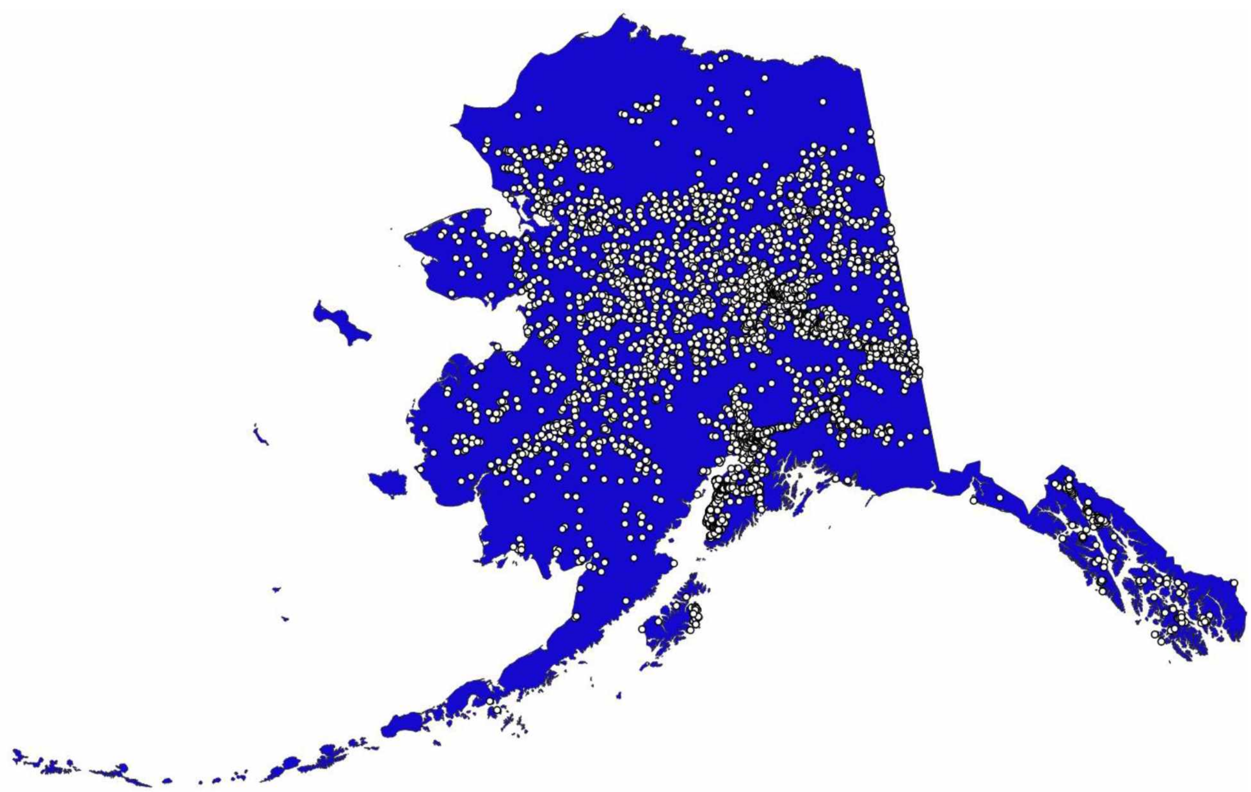

Figure 3.1: Total number of wildfires in Alaska from 2007 to 2015. Points are ignition locations for each wildfire and are not to scale.

In order to most appropriately assess risk and apply spatially oriented pre-suppression actions, Alaskan communities of varying wildfire risk are defined by their respective Community Wildfire

[2] These costs are considered low compared to large wildfire costs in many parts of the contiguous United States, but from both a per capita and budgetary perspective, these costs have the potential to disproportionality impact Alaskan spending.

Protection Plan (CWPP). These CWPPs give exact boundaries for areas where this risk is higher than others and are usually created for individual boroughs. In the Fairbanks North Star Borough, there are three risk zones: high risk, very high risk, and extreme risk. These zone boundaries are often defined by hazardous fuels and topographical features and are spread out across the landscape. The Kenai Peninsula Borough defines four risk areas: low, moderate, high and extreme risk. While these zones do not exactly line up with the zones defined by the Fairbanks North Star Borough, there are clear similarities on the higher risk side. When comparing the two CWPP risk zones in the survey, the top three levels of each are considered equivalent[3]. These risk zones are also considered the objective risk indicators for a neighborhood. Figures for both the FNSB and KPB zones of concern are shown in figures 3.2 and 3.3 respectively.

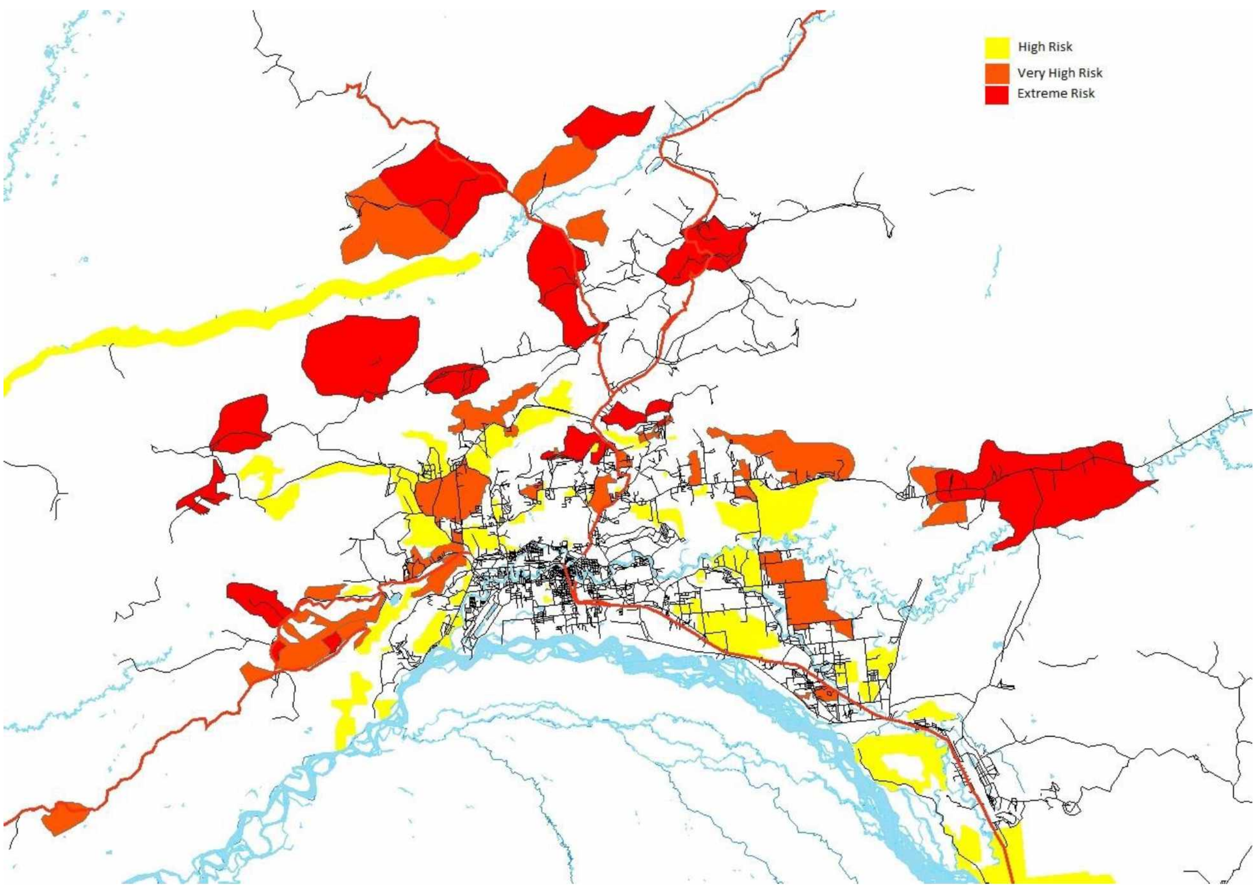

Figure 3.2: Objective risk zones in the Fairbanks-North Star Borough. Areas in yellow are in high risk, orange are in very high risk, and red are in extreme risk.

[3] FNSB 'high' is equivalent to Kenai 'moderate', FNSB 'very high' is equivalent to Kenai 'high', and FNSB 'extreme' is equivalent to Kenai 'extreme'.

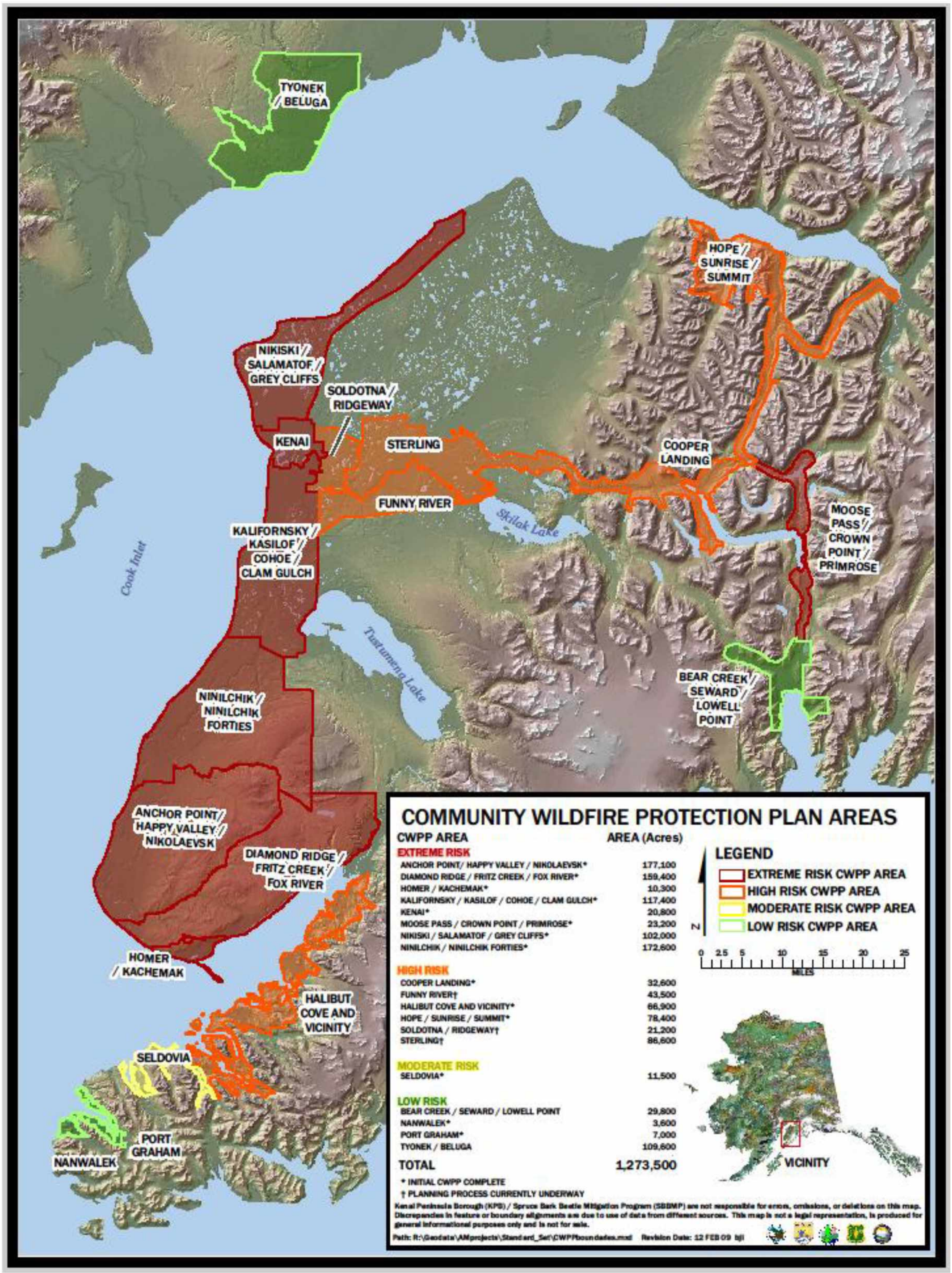

Figure 3.3: Objective risk zones in the Kenai Peninsula Borough. Legend seen below and includes four risk areas, low, moderate, high and extreme risk (Kenai Peninsula Borough 2019)

3.1.2 Under Provision of Wildfire Risk Mitigation

Wildfire mitigation actions are generally underprovided by homeowners in WUI communities (Brenkert-Smith et al. 2006). Pre-suppression[4] activities have been shown to be underutilized and marginally more cost effective than direct suppression actions when fighting wildfire (Lankoande and Yoder 2006). The natural question to answer then is why homeowners underprovide these services, given they directly benefit them. In a WUI context, there is a diverse array of land ownership that make wildfire risk mitigation actions more difficult to manage in the aggregate. Spatially, homeowners who are closer to the open wildland will get the brunt of the damages. It has been shown via simulation that neighborhoods with a buffer strategy[5] to home ignition risk mitigation stop the spread of wildfire through the neighborhoods faster than more spread-out mitigation (Butry and Donovan, 2008). This could potentially create an incentive for homeowners who are further away from the frontlines to free-ride and get indirect wildfire risk reductions without reducing flammable fuels on their own lands. There is also a direct link between the attitudes of people living in WUI locations and the value of the homes. Mitigation activities are seen less in renters, and dwelling cash value is highly motivating at the homeowner level (Collins 2008).

Amenity and privacy values have been shown to drive the under provision of homeowner wildfire risk mitigation actions (Kobayashi et al. 2010, Paveglio et al. 2016). WUI residents are often reluctant to change the landscaping on their property until wildfire is eminent (Brenkert-Smith et al. 2006). This is also shown in a lower WTP for mitigation actions from homeowners on their own property than for public mitigation actions (Holmes et al. 2009). In an experimental setting, there is evidence of a 'crowding out' phenomena where individual homeowners react to increased (or potential increases to) public mitigation activities with lowered mitigation spending, even though there were higher participation rates (Prante et al 2011, Talberth et al. 2006). There is also a belief that protection from wildfire will come in the form of government suppression agencies. A study by Vogt, Winter and Fried (2002) found that trust in the government to protect private property from wildfire was significantly positive. Furthermore, the perception of wildfire risk can drive behavior more than actual wildfire risk. Homeowners often underestimate the true risk levels in their neighborhood, as education initiatives were positively associated with higher rates of homeowner fuel mitigation (Brenkert-Smith et al. 2012). This increased risk information has also been shown to specifically drive mitigation behavior, even more than past wildfire experience (Martin et al. 2009). Even while acknowledging that education increases risk

[4] Defined to be costs associated with planning, prevention, detection equipment, and other similar costs.
[5] Defined to be a spatial arrangement of fuel reduction that focuses on the contact boundary between open wildlands and a WUI community.

mitigation activities, government programs must combat inadequate funding for education-based wildfire programs (Reams et al. 2005). The benefit of reducing wildfire risk by participating in mitigation activities is clear, but these explanations may explain why not enough is being done in many WUI communities. The potential reasons behind the under provision of wildfire mitigation actions were considered while constructing the survey instrument and choice experiment and are reflected in the questions asked.

3.1.3 Homeowner Participation in Mitigation Actions

Homeowners have been shown to participate in wildfire mitigation activities under a variety of circumstances. Even when fully insured, homeowners in WUI communities had significant WTP for wildfire risk reduction via pre-suppression activities (Talberth et al. 2006). While insurance can protect individual homeowners mitigate loss, these protections rarely cover all loses (Winter and Fried 2001). This may seem to contradict earlier comments regarding renters and low cash value homes, since those findings indicate that actions stem from direct economic loss. The idea of non-market losses due to wildfire seem to fill this gap, as they are not protected by insurance policies. WTP estimates for risk reduction via wildfire risk mitigation actions have been attempted in the past. A Contingent Valuation (CV) study estimated a significant WTP in a theoretical market for 50% risk reduction via risk reducing activities (Winter and Fried 2001). WTP for risk reduction via mitigation activities has also been estimated for homeowners from three US states (California, Montana and Florida) in a different CV study (Loomis and Gonzalez-Caban 2008). These estimates were found to be significant and positive, ranging from \$190 to \$500 depending on the individual and location. While useful, CV studies have recently faced significant criticism. First, the cost parameter is sensitive to the monetary scale initially outlined by researchers in a referendum style CV survey. This leads to suggestive prompts on the value of the environmental good in question. Secondly, and most importantly, was their inability to capture the true scope of the environmental loss being avoided (McFadden and Train 2017). Because of this, we need to identify a different approach to estimating WTP that minimizes the difficulties found in CV models. Mixed logit models have been used to assess WUI homeowner wildfire risk reduction preferences in the past (Holmes et al. 2009). Using a stratified random sample of low, medium and high wildfire risk areas, their WTP estimates showed that WUI homeowners in high risk areas were willing to pay more for public wildfire mitigation programs, over their own fuel reduction. Sociodemographic values could identify population segments most in need of financial assistance for mitigation activities that were out of their financial reach. While this study was done in Florida, it may have implications to how much homeowners are willing to pay in similar landscapes and demographics around the country. However, the distinctiveness of Alaskan populations and landscape are suitable for a unique study that fully incorporates the distinctiveness of the state.

Social norms also play a role in how homeowners in WUI areas opt into wildfire risk mitigation activities. Expert analysis of a community's wildfire risk (in the form of a CWPP) is often assumed to be the strongest indicator of risk and risk mitigation information in WUI locations. However, there is evidence that suggests perceptions of risk are affected by informal and non-expert information gained by other community members (Brenkert-Smith et al. 2013). Both a "sense of community" and "community problem solving" were also identified as a resource to increase mitigation activities on homeowner property (Prior and Eriksen 2013). In this vein, social capital is also positively associated with participation in community wildfire programs (Agrawal and Monroe 2006). In terms of WTP, there should be a larger WTP for more neighborhood participation in communities with large amounts of social capital, and for those in the community that are aware of the wildfire risk. Any deviation from this would suggest other factors outweigh this social component.

3.2 Method

3.2.1 Random Utility Model

Discreet choice experiments are a key tool to evaluate the value of nonmarket goods by focusing on a type of stated preference valuation. This is done by estimating the values of individual levels of nonmarket good attributes. By getting these values, we can ascribe overall values to packages of the nonmarket good as they would be seen in the real world. The analysis of discreet choice experiments relies heavily on a Random Utility Model (RUM). Like most applied models, RUMs usually require a set number of assumptions for the results to have any meaning.

The first assumption is that the choices made in the experiment are discreet events that have real world applicability. The respondent chooses between discreet states as designed in the experiment, and not partial, or continuous states. This assumption is met by virtue of the experimental design. The second assumption, and most fundamental, is that all respondents are rational and their choices will always reflect that. Specifically, the model assumes that individual choices are based on the highest utility gain (people are rational utility maximizers). This not only applies to direct utility gains, but also in scenarios in which respondents are minimizing potential loses in the face of uncertainty, in this case, wildfire. This assumption also relies on perfect information to inform rational decision making. In the aggregate, there is the possibility of later choices being affected by non-utility-maximizing behavior if the cognitive burden of the experiment is too large for respondents (straight lining). This issue is primarily addressed by never requiring a response for any portion of the survey and allowing respondents to quit the survey at any time. While theoretical scenarios will always lack a direct commitment from the respondent, choice experiments using RUMs are easier to answer and produce better estimates when compared to CV studies (McFadden and Train 2017).

The last assumption relates to the random component of a respondent's utility. We define this random utility in term of total utility as seen in equation 1.

$$U_{ij} = V_{ij} + e_{ij} \quad (1)$$

The total utility of respondent i given by alternative j (defined as U_{ij}) is comprised of a deterministic component (defined as V_{ij}), and the random component (defined as e_{ij}). The variable V_{ij} is the utility driven by exogenous variables in the alternative j. The deterministic portion could potentially drive the total utility in the face of this perfect information scenario. However, since that rarely happens, we need to look closely at the random component of utility. This utility ultimately drives the overall utility, since the exogenous variables do not affect it, while affecting all respondent's utility identically. When a respondent decides between allowable choice sets, there may be underlying attraction towards one attribute level or another that isn't based on the deterministic utility. The random component of utility e_{ij} is assumed to have a normal distribution in the population. Furthermore, each individual's random utility is also assumed to be independently and identically distributed (IID) for each alternative. In other words, the random component is identically normal across all alternatives, and is independent of other random utilities.

3.2.2 Mixed Logit Model

The focus now becomes estimating the utilities laid out in the previous section. One approach is the mixed logit model (Hensher Greene 2003). Starting from our definition of a RUM, we can break out the deterministic component of utility as such:

$$U_{ij} = V_{ij} + e_{ij} = \beta_{ij}x_{ij} + e_{ij} \quad (2)$$

where β is our preference parameter. In a normal logit model, this parameter would be aggregated. However, in a mixed logit model, we allow for this preference parameter to have a different value for each individual, allowing for individual stochastic utility values. We can further define this utility in terms of the cost involved in making that choice:

$$U_{ij} = V_{ij} + e_{ij} = \alpha_{ij}C_{ij} + \beta_{ij}x_{ij} + e_{ij}$$

where α is the cost parameter (which should be unequivocally negative).

The likelihood that a person with a given β_i chooses an alternative j is given by a standard logit formula:

$$L_{ij}(\beta_{ij}) = \frac{e^{\beta_i x_{ij}}}{\Sigma_n e^{\beta_i x_{in}}} \tag{3}$$

The same will be true when estimating our cost parameter α. Once these parameters are estimated, a simple quotient give us our WTP estimates for all x_{ij}.

$$WTP_{X_{ij}} = \frac{\beta_{ij}}{\alpha_{ij}}$$

Traditional logit models suffer from the Independence of Irrelevant Alternatives (IIA). Because of the way logit predicts probabilities, it often predicts them poorly when other possibilities are added, cross-elasticities aren't equal, or when the substitution of choices is not perfect. The fundamental problem is how logit models handle the random terms. These are assumed to be independent from each other, which can be an incorrect assumption to make. However, a mixed logit model allows for correlated random terms which resolves our IIA problem.

3.2.3 Hierarchical Bayes Estimation

Hierarchical Bayes (HB) estimation[6] will be used to calculate the final marginal utility of choice variable attribute levels. The fundamental idea behind HB is the same as any Bayesian approach; Bayes' theorem.

$$P(\beta|y) = \frac{P(y|\beta)P(\beta)}{P(y)} \tag{4}$$

Our parameter β is the probability of a specific level of an attribute being chosen, and y is the information gained by respondent answers (data). This means that the probability in question can be summarized as the probability of β occurring conditional on the data y. The probability $P(\beta)$ is defined as our prior distribution of β (the probability of β before any new information y), $P(y)$ is the distribution of y occurring (the normalizing distribution or the evidence), and $P(y|\beta)$ as our likelihood distribution (the probability y occurring given β occurs). However, by itself, Bayes' theorem doesn't have the capacity to deal these distributions being variable, often based on latent variables. It also doesn't include a higher order assumption that these choices may also be described by a multivariate normal distribution. This

[6] All material referenced in the Bayesian approach is listed here: (Sawtooth 2016) (Orme 2000) (Johnson 2000)

requires the use of a multi-level analysis of the individual's parameters, which requires a slightly different approach.

HB models implement the use of hyperparameters, and hyperprior distributions. Put simply, the hyperparameter is the highest level of a parameter of the prior distribution, while the hyperprior is the specific distribution of this hyperparameter. Using these, the following framework can be constructed to provide posterior distributions. If we assume that β has a distribution governed by a hyperparameter φ, then we can define the following stages in estimating our posterior.

Stage I: $y_j | \beta_j, \varphi \sim P(y_j | \beta_j, \varphi)$ [the likelihood of y_j occurring given β_j (which has a hyperparameter of φ) has a probability given those values.]

Stage II: $\beta_j | \varphi \sim P(\beta_j | \varphi)$ [the likelihood of β_j occurring given the hyperparameter φ has a probability given those values.]

Stage III: $\varphi \sim P(\varphi)$ [the likelihood of φ being our distribution hyperparameter is given by the a priori probability of φ]

Using Bayes' theorem, and the definition of conditional probability, we can show that in general:
$P(\varphi, \beta_j | y_j) \propto P(y_j | \beta_j)P(\beta_{j,}\varphi)$

and this leads to our 2-stage hierarchical model where our posterior distribution is:

$$P(\beta_j, \varphi | \mathrm{Y}) = \frac{P(Y|\beta_j)P(\beta_j|\varphi)P(\varphi)}{P(Y)} \tag{5}$$

or non-normalized as:

$$P(\beta_j, \varphi | \mathrm{Y}) \propto P(\mathrm{Y} | \beta_j)P(\beta_{j,}\varphi)P(\varphi) \tag{6}$$

Practically speaking, HB estimation of utilities is an iterative process. It needs to consistently add in previous estimates for β in order to come up with better and better utility estimates. Using the principles of Monte Carlo Markov Chain iterations, it allows for other βs to be "borrowed" from other respondents as another reference point to cover the issues of random preferences and their distributions. While this can create a heavy computational load problem, it allows for better estimation of utility parameters by partially pooling responses.

3.2.4 Choice Experiment Design

The RUM assumptions highlight the requirement of sound choice experiment design. Because there is always a random component to a respondent's utility, the requirement for a full factorial design may seem necessary. Even though a full factorial design may be seen as a requirement from the standpoint of our RUM assumptions, we can make statistically sound changes to the design without losing optimality. Minimizing the determinant of the variance matrix[7] leads to D-optimality, ensuring the same effectiveness of a full factorial design with less choice sets. This kind of optimal design becomes a larger and larger necessity due to the nature of the total number of the choice sets. As the total number of attributes increases, the total number of choice sets increases exponentially. This is clearly unrealistic, as the homeowner survey instrument would have needed respondents to view 405 individual choice sets ($3^4 \cdot 5$) for a full factorial design.

Using an adaptive based approach to survey design requires looking at the random utility assumption differently. While before it was necessary to have a D-Optimal design to deal with the random utility, the survey software implements a different technique to insure near optimal choice design[8]. By explicitly asking for favored attribute levels, and discerning unacceptable and required attribute levels, the software can create choice sets of near neighbors while including the normal full range of attribute levels in choice sets. These choices also help inform the hyperparameters in the estimation process. This allows a design that is created while the respondent is actively taking the survey and is customized individually.

Analysis of the choice experiment allows for estimates of utility, and ultimately WTP to be calculated for each of the variables and their levels. The choice experiment asked respondents to choose between different risk reducing scenarios that included five variables with a varying number of attribute levels. Table 3.1 shows the variables selected and their respective levels used in the choice experiment. These variables allowed for choice sets that included a wide range of options, including no costs options, no risk reduction options, and high cost, high risk reduction options. These scenarios also included land management agency involvement, as well as the involvement from neighbors. There is a complex array of variables that influence behavior, so it is important to try and identify the strongest indicators of behavior and attempt to estimate the utility of those factors. This specific configuration of choice variables and levels will also allow for the analysis of altruistic and free riding choice behavior.

As mentioned before, much of the statistical survey design is done by the survey software as the homeowner proceeds through the experiment. Specifically, the three sections of the adaptive choice based conjoint (ACBC) were the “Build your own” (BYO) sections, screener questions, and the choice

[7] Or conversely, maximizing the determinant of the fisher information matrix.
[8] From Sawtooth Software’s help file: ‘The [survey design] algorithm cannot be said to produce optimal designs, but its designs are near-orthogonal, and have proven to work exceptionally well in many methodological studies to date comparing ACBC to standard CBC [predefined D-optimal designs].’

tournament (choice tasks). The BYO section consists of a single screen where all variables and their respective attributes are listed. The screener portion, typically consisting of 6-8 screens is the main tool to whittle down the overall choice sets shown to the respondent. It picks out attribute levels that are more desirable than others. When effectively implemented, these screens reduce the choice sets seen in the choice tournament. Respondents typically saw 6 sets (pages) of 3 choices in the choice tournament, totaling 18 possible combinations. Being able to reduce the total number of pages a respondent sees while keeping statistical efficiency is the most vital improvements to the adaptive choice experiment. The reduction in pages seen helps to keep the cognitive burden low for a survey of this type. Since this survey was going out to a wide range of potential respondents, the length and difficulty of the survey was a constant area of examination. The total time required to take the survey was estimated to be 30-45 minutes. The survey took advantage of the efficiencies in design in order to achieve those times.

3.2.5 Sample Selection

Sound sample selection practices produce the best statistical inferencing when making claims on population behavior. The goal is to feel confident that the sample statistics are unbiased estimates of the population parameters in question. One way to increase the chances of that occurring is to increase our overall sample, and make sure our sample is an accurate representation of the population.[9] Homeowners invited to participate in the survey had to fit several criteria. First, the homeowner needed to live in an area of wildfire risk. Their risk zone, as defined from the CWPP, was noted in their contact letter and in the online survey. Second, since all information about homeowners came from the borough tax database, homeowners needed to have paid taxes on their property. Lastly, the mailing address on file needed to match up with the homeowner's actual mailing address. Any old or outdated information from the respective boroughs made the homeowner of that parcel inaccessible. Once the eligible homeowners were pooled, 1,000 homeowners were randomly selected from each borough (FNSB and KBP). This 1000 homeowner sample was pulled from each borough's wildfire risk population. After the initial contact (via physical letter), homeowners self-selected into the sample by choosing to take the online survey. After multiple follow-ups, a total of 388[10] homeowners participated in the survey (A response rate of 19.4%). This total sample size is sufficient for proper statistical inferencing.

[9] Increasing the sample size has numerous benefits, including reducing the overall variance of the sample, and a simplification of the underlying distribution assumptions, therefore improving statistical tests based on those distributions.

[10] Certain portions of the survey had higher response rates due to the optional nature of the survey questions.

3.2.6 Descriptive Statistics of the Population Sample

Descriptive statistics of survey respondents for age, education level and income were tabulated for each of the fire risk levels (Tables 3.2-3.4). In terms of age, the single largest age group within a risk level was 60 to 69-year-olds in the 'High' risk area (35.6%). Most respondents fell into the 50 to 59 or 60 to 69-year-old categories for age. Income and education values are assumed to be correlated since higher levels of education should lead to higher income levels. In all risk areas, 57.4% of respondents had at least a bachelor's degree. The same trend follows when looking across the different risk zones. The only outlier seems to be a slightly larger upward shift to education levels in the 'High' risk fire zones. When asked about wildfire mitigation activities (Table 3.5), 84% of all respondents indicated that they had pursued at least one mitigation activity on their property. The set of mitigation activities was defined broadly. Actions like clearing a yard of leaf litter, keeping long grasses trimmed, or pruning trees were considered wildfire-mitigating activities (Table 3.6). Responses to mitigation activity questions were incorporated into section III of the Alaska Wildfire Coordinating Group Wildfire Risk Rating for Homes in the Wildland Urban Interface spreadsheet. In terms of structure preparedness (Table 3.7), respondents from both regions fell in the 'moderate' category. Breaking down responses across wildfire risk showed that those in the 'Very High' risk zones were the most likely to have taken risk mitigation action, with 87.2% having done some mitigation action. The other risk zones ('High' and 'Extreme') still had 'Yes' responses above 80%, which was shown to be statistically equivalent (ANOVA p value=0.413).

If the respondent indicated that they had done some mitigation activities, they were asked to specify their level of involvement (Table 3.6). Only a small percentage of respondents had installed non-combustible materials to the exterior of their home. Fire resistant siding has the lowest selection rate, with only 6.9% of respondents indicating they have installed it in their homes. The next two lowest were related to roof upgrades, with only 11.7% installing screening over roof vents and 13.1% installing a chimney spark arrester. Instead, this section was dominated by the vegetation options. 71.7% of respondents indicated that they cut down dead or decaying trees from their properties. The next two highest responses came from pruning and trimming trees and bushes (60.5% of respondents) as well as regularly clearing the first 10 feet of land around their home of light brush (54.5% of respondents). The most direct explanation for this discrepancy in activity type is the fundamental reasoning behind these homeowner activities. The installation of fire-resistant materials on someone's home only provides one service to the homeowner, which is reducing the ignition probability to the home in the event of an external fire. Vegetative removal options however can provide other services to the homeowner. The amenity values associated with pruned and cut vegetation may often outweigh the fire mitigation values associated with these activities (Paveglio et al. 2016). The large initial values for mitigation activity may just reflect amenity values and not activities based on wildfire risk reduction. Care should also be taken when comparing these two activities, as there are significant price and time[11] differences in these types of mitigation actions.

Keeping a defensible space around a home is a key component in protecting homes from wildfire risk. This includes keeping flammable fuel sources, and unmaintained vegetation away from the structure, and preferably, at least 100ft away from the home. Most respondents indicated that they kept fuel sources relatively close to their home (Table 3.8). These values change a bit when looking at the risk breakdowns, as those in the 'Extreme' fire risk zone tended to keep unmaintained vegetation further away than those in relatively lower risk areas. When directly asked how land management agencies should reduce hazardous fuels from public lands in the area, the responses were dominated by mechanical thinning to create shaded fuel breaks (Table 3.9). In terms of wildfire mitigation, removing more fuel is more beneficial in terms of increasing changes to wildfire behavior. However, this seems to be a secondary consideration when viewed from the perspective of the survey respondents. Across risk areas, there wasn't much variation in this preference. There was a slight decrease to the percentage of people who preferred mechanical thinning as risk increased. Because thinned fuel treatments are much more expensive than cleared fuel breaks, this high level of preference may only indicate the desire for more valuable landscaping options, as the respondents are not making any economic tradeoffs for the mitigation action. This will be directly addressed when discussing choice experiment results.

3.3 Choice Experiment Results and Discussion

The results for all WTP estimates are shown in Tables 3.10a-3.10c. Based on responses to survey questions, as well as geographic location and sociodemographic data, WTP estimates changed based on the inferred qualities of those interactions.

3.3.1 All Respondents

Using all respondents (n=358) to the choice experiment, WTP estimates are a baseline for all other group interactions. These estimates represent all Alaskan households who completed the survey, making no distinction to location or other demographic information. These respondents have preferences that are generally reflective of behaviors identified in other studies (Brenkert Smith et al. 2006). Specifically, that amenity values and social norms of contribution are acknowledged. The number of neighbors mitigating (*neigh0, neigh1-4, neigh5+*) their own property was significant and show preference for mitigation. While neighbor mitigation was beneficial for adjacent landowners from a risk perspective, too much of this activity was less preferred, as seen in the smaller WTP estimates for *(neigh5+)*. WTP

[11] Time differences include both the frequency of the activity, as well as the durability of the home materials.

estimates are similar for (*neigh0)* and *(neigh5+)*, suggesting that this middle ground provides some protection, while keeping some of the inherent value from flammable fuels. While this potentially goes against a social norm argument, it may merely indicate that individual level amenity-based incentives may outweigh the social component in the aggregate.

Public lands in WUI communities may provide amenity values to residents but may also provide wildfire risk mitigation when properly treated. While this public land could be managed under a myopic risk mitigation perspective, the preferences of nearby residents are crucial to building cooperative management decisions. Even when preferences do not align perfectly between homeowners and land management agencies, this input can provide information to help land managers better understand the impacts of their decisions. Both thinned and clear-cut fuel treatments have been shown to beneficially change wildfire behavior in modelling settings (Little et al. 2018). However, for the Alaskan residents surveyed, the type of mitigation done on nearby public lands showed no ordinal value based on WTP estimates. There is a very strong preference for thinned (*thin*) fuel treatments, over clear cut (*clear)*, or even no mitigation (*nomit)*. This indicates that respondents would rather have the increased risk of flammable fuels on nearby lands, than have flammable fuels completely removed in portions of those lands. Alternatively, homeowners would rather produce this risk reduction themselves (at the WTP cost) then have the risk reduction come from the form of reduced fuels. One anecdotal explanation for this is the presence of permafrost soils in Alaska. These soils are perpetually frozen and provide stability to structures built on top of them. If these soils are then exposed to direct sunlight from clear cutting, they may change the structural dynamic in the surrounding area. Homeowners have more control over the way they reduce fuels on their own land, so this may be preferable. Another explanation is that the amenity values lost from clear cutting are valued higher than the expected risk reduction to the homeowners. This can be seen by the much larger WTP estimates for *(nomit)* over *(clear)*[12]. Thinned fuel treatments *(thin)* were the clear preference for homeowners, providing both some level of amenity value and permafrost protection. While the higher WTP for thinned fuel treatments were apparent, these values may or may not converge with the much higher increased costs of these treatments, which can reach $8,000 per acre in Alaska (St. Clair 2006). These results also mirror the Holmes et al. study (2009) where WTP was larger for thinned public mitigation over own risk reduction, as well as qualitative analysis from Paveglio et al. (2016).

[12] As mentioned before, our baseline WTP levels were based on lowest preference levels, not community status quo. Meaning that a WTP here for the status quo of no action *(nomit)* is a WTP over the least preferred option, which was clear cutting *(clear)*.

On the surface, WTP estimates for risk reduction variables tell an obvious story; respondents have larger WTP estimates for larger amounts of risk reduction. Even when comparing *(ownrisk)* to *(neighrisk),* the fact that respondents value their own risk reduction over their neighbor's risk reduction was presumed from a utility theory perspective a priori. However, these WTP estimates for risk reduction provide interesting results in the social context of altruism and free riding. Because the neighbor risk reduction variable was defined as risk reduction to the neighbors only, the WTP measures here are indicative of altruistic support of other neighborhood residents. Even in the face of common-sense realizations of shared neighborhood risk reduction, 8.37% (144 out of 1720) of all choice sets selected included an altruistic element. These choice sets were ones that had some preparation cost and resulted in no risk reduction to one's own property *(ownrisk0)*. Out of these choice sets selected, there was a higher frequency for lower costs and higher neighbor risk reduction as seen in Table 3.11. Because there was no correlation between *(cost)* and *(neighrisk)*, this suggests that this distribution is independent of the actual amount of *(neighrisk),* and these altruistic choices occur similarly for all *(neighrisk)* levels. This very much aligns with traditional utility theory, as well as warm glow studies done on contingent valuation surveys (Nunes & Schokkaert 2003)[13]. Traditional utility theory suggests that in order to combat the drop in individual utility from the cost, they would need to make up for it either from a relatively lower cost or more altruistic gain (neighbors risk increases) in order to maximize utility for a single choice. Free riding behavior was also observed in 20.6% (354 out of 1720) of choice set selections. These choice sets were ones that cost the respondent no money, but gave them some amount of risk reduction, either (*ownrisk25)* or *(ownrisk50).* While much of the utility gain is presumably due to the lack of cost, some of the preferences within the freeriding choices provide insight. Table 3.12 shows the frequency table for own risk and neighbors' risk. Correlation between the *(ownrisk)* and *(neighrisk)* variables within these responses indicates that these free riding choices tended to match risks (25% reduction for both or 50% reduction for both). In other words, it was less preferred for these free riding choices to include a situation where *(ownrisk)* was larger than *(neighrisk)* or vice versa. This is evidence of a restrained type of free riding.

3.3.2 Differences in Borough Respondents

Because the survey was sent out to two distinct Alaskan communities, WTP estimates can be calculated to compare how these homeowners value risk reduction differently. Respondents from the Fairbanks North Star Borough (FNSB, n=226) were analyzed separately from Kenai Peninsula Borough respondents (KPB, n=131). Apart from public land clearing, FNSB respondents had WTP estimates that

[13] Nunes and Schokkaert also assert that the inclusion of warm glow influence to WTP estimations is perfectly legitimate, as respondents may weigh the utility gained from different social states as they please.

were either similar to, or larger than the respondents from the KPB (Table 3.10c). Specifically, moderate neighbor mitigation *(neigh1-4)* had a similar WTP to that of KPB respondents, but aggressive neighbor mitigation *(neigh5+)* WTP was much less in the KPB. Respondents in the KPB preferred *(neigh0)* over (*neigh5+),* indicating that robust community participation was not valued as highly as in the FNSB. However, when evaluating interaction terms, public land mitigation was valued higher in the KPB for both *(thin) (FNSB* $1290, KPB $1731*)* and *(none) (FNSB$659, KPB$912)*. The variables *(ownrisk)* and *(neighrisk)* had a higher WTP across all levels in the FNSB (*ownrisk25: $1133 ownrisk50: $1296 neighrisk25: $667 neighrisk50: $689)* over the KPB (*ownrisk25: $854 ownrisk50: $945 neighRisk25: $453 neighRisk50: $544)*. This may suggest that while the ordinal value of variable levels stay the same, the overall perception of variables is seen as less desirable. KBP respondents valued moderate neighbor mitigation similarly to the FNSB respondents. However, these respondents valued aggressive fuel treatment much less, as seen by the negative WTP estimate. When comparing the two locations we see strong difference in preferences, with differences in one area being opposite those in another. While this may be a consequence of the grouping themselves (the total sample size is exactly equal to the sum of each locations sample sizes), the magnitude of these changes is still of interest. This combined with the fact that we see similar values for some attribute levels suggest that there are indeed significant differences in the way the two regions view wildfire risk reduction.

3.3.3 Self-Identification of Risk

Self-identification of wildfire risk changed the WTP for risk reduction. Those who self-identify as having a 'High Risk[14]' where compared to those who self-identify as having a 'Low Risk[15]'. There is a general shift upwards for WTP for these 'High-Risk' respondents (n=161) when compared to both the baseline group and the low risk group. Specifically, neighbors mitigating, and risk reduction (for both *ownrisk* and *neighrisk*) had significantly higher WTP values. These results show that the risk reduction from fuel removal is valued more in people who feel more threatened by wildfire than the baseline group. The one exception was the WTP for *(nomit)* where there was a reduction of almost 40%. This may be explained by the reduced amenity or inherent value in surrounding vegetative fuels by 'High-risk' respondents, due to their own risk assessment. The 'Low Risk' respondents (n=142) showed a similar general decrease for WTP measures. Risk reduction for these respondents were valued much less than the

[14] When asked 'Which statement best describes your perception of the risk wildfire presents to your home?' these respondents answered either: 'Wildfire will threaten my home in the next 10 years' or 'Wildfire will probably threaten my home in the next 10 years'.
[15] When asked 'Which statement best describes your perception of the risk wildfire presents to your home?' these respondents answered either: 'Wildfire will not threaten my home in the next 10 years' or 'Wildfire will probably not threaten my home in the next 10 years'.

baseline for neighbors mitigating, *(ownrisk)*, as well as *(neighrisk)*. Public land fuel reduction type was again an exception with a larger WTP for (*thinned*) and *(none)* when compared to the baseline.

3.3.4 Insurance

Responses to the question ‘How much do you pay per month for your homeowners’ insurance?’ were used to see how insurance premium affects the value of homeowner wildfire risk mitigation. The respondents were categorized by how much they paid in home insurance premiums. The groups were ‘low insurance’ (n=141), defined by paying home insurance premiums between $1 and $100, and ‘high insurance’ (n=152), defined by paying home insurance premiums of more than $100 per month. There was also a small sample of respondents who did not have any homeowners insurance at all (n=31). WTP values for each group have been calculated and are again shown in Table 3.10a. The estimates for ‘Low Insurance’ respondents are similar to the baseline estimates for neighbors mitigating, public land clearing, and neighbors risk reduction. WTP for *(ownrisk)* was smaller than the baseline. ‘High Insurance’ respondents valued neighbor mitigation less than the baseline group, with a negative WTP for *(neigh5+)*. For all other variables, WTP was larger than the baseline group, suggesting that even with a large amount of home protection via insurance, there is still significant WTP for risk reduction. It should be noted that insurance premiums are directly correlated with home value, so these WTP may reflect that, as well as non-insurance covered losses. Estimates for those who had no insurance are also listed, but due to the relatively small sample, these estimates may not be wholly reflective of that population.

3.3.5 Previous Experience with Wildfire

Lastly, respondents were shown a question that asked if any household members (including themselves) had direct experience with wildland fires[16]. Respondents were able to choose any or all of the three options, which included:

- evacuated home because of wildland fire
- suffered property damage because of wildland fire
- witnessed wildland fire, observed smoke, or other effects of wildland fire

They were then grouped by those who selected at least one of these options (n=303), and those who did not select any (n=55). Those that had some direct experience had WTP estimates that were very similar to the baseline (Table 3.10c). Neighbor mitigation and public land mitigation variables all had very similar WTP estimates. *(ownrisk) and (neighrisk)* had increases, especially *(ownrisk50)*. Seeing as this group had

[16] Question text: Which of the following situations regarding wildfire have you or someone in your household experienced?

a large sample proportional to the entire sample, it isn't surprising that the WTP estimates are similar. However, the small risk-based changes suggest that those who have had some direct experience with wildfires prefer risk reduction more than the baseline. Those without any experience had almost no preference for any neighbors mitigating their land, far lower than the baseline. For these respondents, *(neigh5+)* was preferred less than *(neigh0)*. WTP for public land mitigation was also lower than the baseline. WTP values for *(ownrisk) and (neighrisk)* were significantly lower; about half of the baseline values. This may suggest that those without any direct experience with wildfire do not fully appreciate the risk due to wildfire. This theme is particularly suitable for future research, as the 2019 Shovel Creek fire (a WUI community in our sample area) required evacuation and should significantly increase the number of respondents with direct experience with wildfire.

3.4 Conclusion

The choice experiment, survey, and subsequent analysis all provide useful information to wildfire professionals across Alaska. There is evidence that certain homeowners would be incentivized to do mitigation activities by certain types of LMA activity. This would also include a reduction to the dangers of wildfire both to their own homes and well as their communities at large. Areas with the highest risk should be targeted with a specific risk analysis and LMA shaded fuel treatment plans to entice homeowners to mitigate on their own property. Anecdotal evidence suggests that the shaded treatments are needed due to the Alaskan permafrost, and quantitative evidence suggests the draw of amenity values on the shaded vegetation itself. However, this point needs to be addressed in order to most efficiently use resources to motivate homeowner mitigation. Also, the potential bias in the statistical estimation from the larger than normal education and income levels should be examined in further detail as well. Any of these issues can be addressed with future survey and choice experiment work. The foundation for addressing the needs and tastes of homeowners now exists and can be modified to answer an ever-growing list of other possible research questions. Wildfire professionals depend on sound research to inform their decision making. Other areas of the state could also be included in future surveys to increase the chances of a more even sample distribution. While this analysis provides a great foundation, Alaskan WUI communities will continue to require research to ensure they continue to thrive for decades to come.

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Table 3.1: Variables and variable levels used in choice experiment. The cost variable had five levels ranging from $0 to $2,000. The remaining variables had three levels and varied.

Variable	Variable Level 1	Variable Level 2	Variable Level 3	Variable Level 4	Variable Level 5
Cost of preparing your property	No action on your property	$500	$1,000	$1,500	$2,000
Number of nearby neighbors preparing their property	No neighbors preparing their property	1-4 neighbors preparing their property	5 or more neighbors preparing their property		
Fuel treatments on neighboring public lands	No fuel treatment on nearby public lands	Nearby public lands have been thinned to create shaded fuel breaks	Nearby public lands have cleared fuel breaks where all trees have been removed		
Reduction in wildfire risk to your property	No reduction in wildfire risk	25% reduction in risk over 10 years (from a 20/1,000 chance to a 15/1,000 chance)	50% reduction in risk over 10 years (from a 20/1,000 chance to a 10/1,000 chance)		
Reduction in wildfire risk to your neighbors	No reduction in wildfire risk	25% reduction in risk over 10 years (from a 20/1,000 chance to a 15/1,000 chance)	50% reduction in risk over 10 years (from a 20/1,000 chance to a 10/1,000 chance)		

Table 3.2: Age demographic data counts broken down by risk zone. Total counts for each zone and age group are also included.

Age	High Risk	Very High Risk	Extreme Risk	All Risk Levels
Younger than 20 years old	0	0	0	0
20-29 years old	3	1	3	7
30-39 years old	14	13	20	47
40-49 years old	12	27	23	62
50-59 years old	18	41	27	86
60-69 years old	31	37	27	95
70-79 years old	8	17	8	33
80-89 years old	1	2	1	4
90 years old or older	0	0	0	0
TOTAL	87	138	109	334

Table 3.3: Education demographic data counts broken down by risk zone. Total counts for each zone and education group are also included. Also includes education levels by percentage in risk zone.

What describes the highest education level you have completed?	High Risk	Very High Risk	Extreme Risk	All Risk Levels
did not finish High School	1	2	1	4
high school diploma	5	7	10	22
some college	14	25	24	63
associate degree	6	17	12	35
professional certification	4	5	9	18
bachelor's degree	26	46	35	107
graduate degree	22	25	16	63
doctorate/PhD degree	8	11	2	21
TOTAL	86	138	109	333
did not finish High School	1.16%	1.45%	0.92%	1.20%
high school diploma	5.81%	5.07%	9.17%	6.61%
some college	16.28%	18.12%	22.02%	18.92%
associate degree	6.98%	12.32%	11.01%	10.51%
professional certification	4.65%	3.62%	8.26%	5.41%
bachelor's degree	30.23%	33.33%	32.11%	32.13%
graduate degree	25.58%	18.12%	14.68%	18.92%
doctorate/PhD degree	9.30%	7.97%	1.83%	6.31%

Table 3.4: Income demographic data counts broken down by risk zone. Total counts for each zone and income group are also included.

What is the total gross (before taxes) income for your household?	High Risk	Very High Risk	Extreme Risk	All Risk Levels
Less than $10,000	1	1	3	5
$10,000-$19,999	4	6	2	12
$20,000-$29,999	1	5	6	12
$30,000-$39,999	1	5	6	12
$40,000-$49,999	2	6	5	13
$50,000-$59,999	5	15	5	25
$60,000-$69,999	5	9	10	24
$70,000-$79,999	11	17	8	36
$80,000-$89,999	5	14	10	29
$90,000-$99,999	6	10	11	27
$100,000-$109,999	8	10	9	27
$110,000-$119,999	4	5	3	12
$120,000-$129,999	7	4	6	17
$130,000-$139,999	6	8	6	20
$140,000-$149,999	5	2	4	11
Greater than $150,000	12	18	10	40
TOTAL	83	135	104	322

Table 3.5: Responses to mitigation action taken broken down by risk zone. Total counts and percentages for each zone are also included.

Have wildfire mitigation activities been done on your home or property?	High Risk	Very High Risk	Extreme Risk	All Risk Levels
Yes	76	136	103	315
No	17	20	23	60
TOTAL:	93	156	126	375
% Yes	81.72%	87.18%	81.75%	84.00%
% No	18.28%	12.82%	18.25%	16.00%

Table 3.6: Counts of specific risk mitigation actions taken by homeowners. Respondents could select as many actions as applied. Includes percentages of both those who had done some action (Selected) and from all respondents (Selected from Total Respondents).

	Selected	Selected	Selected from Total Respondents
installed fire resistant siding	26	8.25%	6.93%
installed fire resistant roofing	120	38.10%	32.00%
installed screening over roof vents	44	13.97%	11.73%
installed a chimney spark arrester	49	15.56%	13.07%
widened the road leading to property	83	26.35%	22.13%
regularly cleared leaves from roof to reduce wildfire risk	122	38.73%	32.53%
regularly cleared leaves from roof for appearance purposes	70	22.22%	18.67%
regularly cleared first 10 feet of land around your home of light brush	193	61.27%	51.47%
regularly cleared first 50 feet of land around your home of light brush	152	48.25%	40.53%
regularly cleared first 100 feet of land around your home of light brush	59	18.73%	15.73%
regularly cleared leaves from yard for appearance purposes	129	40.95%	34.40%
pruned and trimmed trees and bushes	227	72.06%	60.53%
cut down dead or decaying trees	269	85.40%	71.73%
thinned dense areas of vegetation	187	59.37%	49.87%
mowed long grasses to reduce wildfire risk	158	50.16%	42.13%
mowed long grasses for appearance purposes	166	52.70%	44.27%
other: [Respondent Specify]	40	12.70%	10.67%

Table 3.7: Alaska Wildland Fire Coordinating Group preparedness scores by region. Respondents were scored based on survey responses.

Region	Preparedness Score (Out of 25)
All	13.23
FNSB	13.10
KPB	13.54

Table 3.8: Responses to defensible space question broken down by risk zone. Total counts for each zone and defensible space are also included. Also includes defensible space levels by percentage in risk zone.

How close is the nearest fuel source to your home? Please include overgrown, dense, or unmaintained vegetation, as well as non-vegetative fuel sources such as firewood, fuel tanks, wood pellets, or other materials that could easily catch on fire.	High Risk	Very High Risk	Extreme Risk	All Risk Levels
within 0-10 ft. from home	24	54	28	106
within 10-30 ft. from home	42	59	42	143
within 30-100 ft. from home	27	38	51	116
further than 100 ft. from home	0	4	3	7
I don't know	0	2	2	4
TOTAL	93	157	126	376
% within 0-10 ft. from home	25.81%	34.39%	22.22%	28.19%
% within 10-30 ft. from home	45.16%	37.58%	33.33%	38.03%
% within 30-100 ft. from home	29.03%	24.20%	40.48%	30.85%
% further than 100 ft. from home	0.00%	2.55%	2.38%	1.86%
I don't know	0.00%	1.27%	1.59%	1.06%

Table 3.9: Responses to fuel treatment question broken down by risk zone. Total counts for each zone and fuel treatment type are also included. Also includes fuel treatment type by percentage in risk zone.

If public agencies were to perform hazardous fuel reduction around your neighborhood, which of the following methods would you prefer?	High Risk	Very High Risk	Extreme Risk	All Risk Levels
cleared fuel break	7	17	14	38
mechanical thinning	74	114	89	277
no fuel treatments	7	13	11	31
TOTAL	88	144	114	346
cleared fuel break	7.95%	11.81%	12.28%	10.98%
mechanical thinning	84.09%	79.17%	78.07%	80.06%
no fuel treatments	7.95%	9.03%	9.65%	8.96%

Table 3.10a: WTP estimates for all respondents, subjective risk and insurance.

	All respondents	High Risk	LowRisk	High Insurance	LowInsurance
No neighbors preparing their property *(Neigh0)*	$0.00	$0.00	$0.00	$0.00	$0.00
1-4 neighbors preparing their property *(Neigh1-4)*	$319.24	$775.97	$111.73	$232.54	$316.81
5 or more neighbors preparing their property *(Neigh5+)*	$14.78	$431.21	($229.31)	($85.61)	$43.69
Cleared *(clear)*	$0.00	$0.00	$0.00	$0.00	$0.00
Thinned *(thin)*	$1,456.56	$1,586.99	$1,542.45	$1,752.33	$1,438.50
None *(nomit)*	$764.58	$474.99	$1,068.97	$852.10	$876.84
No reduction in wildfire risk *(ownrisk0)*	$0.00	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(ownrisk25)*	$1,050.02	$1,502.92	$814.63	$1,337.78	$814.43
50% reduction in risk over 10 years *(ownrisk50)*	$1,179.36	$1,659.29	$903.39	$1,524.68	$901.60
No reduction in wildfire risk *(neighrisk0)*	$0.00	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(neighrisk25)*	$596.27	$1,037.47	$330.02	$637.17	$586.21
50% reduction in risk over 10 years *(neighrisk50)*	$652.91	$1,186.82	$351.50	$729.48	$627.70

Table 3.10b: WTP estimates for all respondents and by changes in income.

	All respondents	LessThan50k	50-100k	MoreThan100k
No neighbors preparing their property *(Neigh0)*	$0.00	$0.00	$0.00	$0.00
1-4 neighbors preparing their property *(Neigh1-4)*	$319.24	$726.40	$266.11	$362.90
5 or more neighbors preparing their property *(Neigh5+)*	$14.78	$501.51	($59.84)	$48.03
Cleared *(clear)*	$0.00	$0.00	$0.00	$0.00
Thinned *(thin)*	$1,456.56	$1,574.27	$1,220.94	$1,738.22
None *(nomit)*	$764.58	$839.10	$395.27	$1,010.83
No reduction in wildfire risk *(ownrisk0)*	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(ownrisk25)*	$1,050.02	$899.67	$999.42	$1,377.32
50% reduction in risk over 10 years *(ownrisk50)*	$1,179.36	$1,191.78	$1,207.60	$1,454.31
No reduction in wildfire risk *(neighrisk0)*	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(neighrisk25)*	$596.27	$459.70	$677.67	$688.28
50% reduction in risk over 10 years *(neighrisk50)*	$652.91	$794.19	$722.19	$758.19

Table 3.10c: WTP estimates for all respondents, borough differences and experience with wildfire.

	All respondents	FNSB	KPB	Direct Experience	No Direct Experience
No neighbors preparing their property *(Neigh0)*	$0.00	$0.00	$0.00	$0.00	$0.00
1-4 neighbors preparing their property *(Neigh1-4)*	$319.24	$314.31	$315.23	$395.77	$8.49
5 or more neighbors preparing their property *(Neigh5+)*	$14.78	$85.88	($162.43)	$38.02	($116.87)
Cleared *(clear)*	$0.00	$0.00	$0.00	$0.00	$0.00
Thinned *(thin)*	$1,456.56	$1,290.49	$1,730.82	$1,480.52	$1,222.02
None *(nomit)*	$764.58	$659.18	$912.40	$771.92	$610.73
No reduction in wildfire risk *(ownrisk0)*	$0.00	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(ownrisk25)*	$1,050.02	$1,133.00	$853.81	$1,197.19	$454.43
50% reduction in risk over 10 years *(ownrisk50)*	$1,179.36	$1,296.07	$944.74	$1,345.29	$518.35
No reduction in wildfire risk *(neighrisk0)*	$0.00	$0.00	$0.00	$0.00	$0.00
25% reduction in risk over 10 years *(neighrisk25)*	$596.27	$667.09	$453.37	$677.90	$305.72
50% reduction in risk over 10 years *(neighrisk50)*	$652.91	$689.04	$543.56	$716.20	$413.86

Table 3.11: Frequency table of altruistic choice sets where *(ownrisk0)* was selected. Frequencies were not correlated with changes in *(neighrisk)* category (χ^2 *p* value = 0.395)

	\$500	***\$1000***	***\$1500***	***\$2000***	**Total**
Neigh0	8 (34.8%)	9 (26.1%)	2 (8.7%)	7 (30.4%)	23 (100%)
Neigh25	21 (41.2%)	16 (31.4%)	5 (9.8%)	9 (17.6%)	51 (100%)
Neigh50	33 (47.1%)	13 (18.6%)	11 (15.7%)	13 (18.6%)	70 (100%)
Total	62	35	18	29	144

Table 12: Frequency table of free-riding choice sets where *(ownrisk)* was not 0% and cost was \$0. Frequencies were correlated with changes in *(ownrisk)* category (χ^2 *p* value < 0.001)

	Neigh0	***Neigh25***	***Neigh50***	**Total**
ownrisk25	35 (26.1%)	59 (44.0%)	40 (29.9%)	134 (100%)
ownrisk50	28 (12.7%)	81 (36.8%)	111 (50.5%)	220 (100%)
Total	63	140	151	354

Chapter 4 The Effect of Fuel Treatments on the Suppression Costs of Large Alaskan Wildfires[1]

Abstract

The State of Alaska has unique challenges when stemming the social and economic costs of wildland fires. The total land mass and relatively low population densities of the state lead to large communities living in the Wildland Urban Interface. Homeowners in these areas are more susceptible to wildfire risk and face a larger threat to their homes and property. While wildfires that directly threaten these communities are abated with direct suppression efforts once discovered, the costs of suppression efforts can have staggering effects to state budgets. The costs of these large, open land wildfires were examined in a two stage least squared instrumental variable framework. Land management agencies often use fuel treatment locations to leverage suppression resources when available. They are anecdotally associated with cost efficiencies and expenditure savings by stopping wildfires sooner. By examining over 160 large Alaskan wildfires from 2007-2015, there is evidence that fuel treatments do not reduce wildfire suppression expenditures in the state in the aggregate. Costs were primarily driven by management option zones, the size of the fire, and several ecological factors. Even though fuel treatments weren't cost saving in general, understanding the suppression costs of Alaskan wildfires can potentially lead to better budgetary efficiencies by most appropriately allocating scarce funds to where it can do the most good.

4.1 Introduction

4.1.1 Alaskan Perspective on Wildfire

Wildland fire has been steadily increasing in frequency and severity for decades (Kasischke & Turetsky 2006). While frequent wildfire years are often episodic, climate variables seem to be driving this increase in frequency and scale (Brown et al. 2004, Flannigan et al. 2009). Alaska is disproportionately affected by these climate dynamics and resulting wildfires due to its large land area. The spatial dimensions of the state required an interagency group of Alaska wildfire suppression agencies to create distinct suppression response zones (Alaska Department of Natural Resources: Division of Forestry 2019a). These suppression management zones are defined by the potential risk to people and property from wildland fire. These zones guide wildfire managers to make decisions based on predetermined plans to address a wildfire ignition. The zones range from limited zones that warrant almost no suppression

[1] This chapter is currently being prepared externally for academic journal publication. Other authors on that manuscript include Joseph Little (University of Alaska Fairbanks), Stacy Drury (USDA - US Forest Service), Randi Jandt (University of Alaska Fairbanks) and Brock Lane (University of Alaska Fairbanks).

response, to critical zones where a rapid and an extensive suppression response is imperative (Figure 4.1).While large fires in limited and modified are often left to burn under supervision, any increase in frequency, severity, or proximity to population centers can sharply increase the need for suppression resources, as well as funds to cover the increased expenditures. Projections of wildfire costs in Alaska over the next century lie between one and two billion dollars, with an annual average of approximately 60 million per year (Melvin et al. 2017). This not only presents a budgetary problem for the state, but a policy issue for state decision makers. Since sound policy should be born from quality scientific research, a thorough understanding of the costs of Alaskan wildfire and what drives them will be needed to mitigate potential fiscal impacts. Economic cost modeling will be crucial to examine the variability of expenditures used to suppress Alaskan wildland fires. This point is even more pertinent given the current budgetary predicament the state faces.

4.1.2 The Cost of Wildfire Suppression

The current wildfire suppression paradigm across the US is one that responds to large wildfire as a critical emergency when it threatens life and property. This is seen in the proportionality of suppression costs and number of nearby homes (Gude et al. 2013). In this context human lives are priceless, and we should expend every considerable resource to save people from wildfire. While this point is rarely debated, a myopic view may neglect the finite budgetary resources needed to respond with full force to threatening wildfire. This is not a new problem, as long-term upward trends have been seen in wildfire suppression cost data going back to the 1970's (Calkin et al. 2005, Gorte 2013). Cost efficiencies are of critical need in Wildland Urban Interface (WUI) locations, where there is the largest risk of loss from wildland fire. While the most obvious choice to model the costs of wildfire are ecological and climate variables, there are significant social variables that may influence suppression costs via incident decision making (Donovan et al. 2011, Thompson 2014). The non-social predictors of these rising suppression costs include increased biomass, drier and more dense forest understories, aggressive low intensity wildfire suppression, higher temperatures, drought, early snowmelt, and invasive pests. While there is little to be done in the local environment to impact global climate variables in the short term, reducing bulk biomass via fuel treatments has become a popular option for wildfire risk management. Fuel treatments represent a hybrid of an ecological and social variable, as it changes the physical characteristics of flammable fuels, as well as provide incident commanders an additional resource to potentially leverage when considering suppression tactics. Because wildfire managers can behave non-optimality when ordering resources for fires (Wibbenmeyer et al. 2013), examining the role of fuel treatments in suppression expenditures is an examination of both physical and social factors. Fuel treatments have been shown to be a significant variable in resource ordering for wildfire managers in a small sample expert elicitation framework (Little et al. 2018). If these trends were to exist in the larger population of wildfire managers and incident commanders, it could lead to more informed decision making and potentially suppression cost savings.

4.1.3 Wildfire Time Trends in Alaska

As previously mentioned, the frequency and severity of wildfires are increasing temporally on a national level. The trends are less clear for the State of Alaska. Statewide data was collected from the Alaska Department of Forestry for the aggregate number and area of wildfires burned both on state-controlled lands and statewide fires. Table 4.1 shows these values, while figures 4.2 and 4.3 give us a visual representation of the data. There were no statistically significant time trends found in acres burned per year in either DOF fires, or all statewide fires. We see the same lack of trend when breaking out the acreage by protection zone. The lack of a linear time trend suggests that the probabilistic nature of wildfire, mixed with the large number of low risk fires make these values driven by short-term episodic changes in climate and fuels. The seasonal changes for precipitation and lightning strikes are like those for wildfire seasonality, suggesting a non-linear trend in the short-term (Kasischke et al. 2002). The number of fires did have a significant time trend, but it was trending downwards in time. This downward tendency is counterintuitive, as we should either see the increases seen nationally, or no time trend. One potential explanation for this discrepancy has to do with the size of the state. There are two categories for wildfires causes as defined by the state: human and lightning. While more wildfires are started by human means, more acres are burned from wildfires ignited by lightning in Alaska (Alaska Department of Natural Resources 2019b). This could explain why there is no short-term linear time trend in the total acres burned, and why the total number of wildfires may be reducing over our timeframe. Presumably, any outreach and capacity building informational programs related to reducing wildfire ignition must target human caused wildfires. No informational campaigns can reduce the number of randomly probabilistic wildfires attacking the Alaskan landscape from lightning strikes. The total area of the state increases the probability that lightning will strike somewhere within its borders. This coupled with small population centers makes most of these fires no threat to human life or property. These fires then make up the bulk of the acres burned as they had little to no suppression resources used on them. Suppression cost trends for the analyzed wildfire data are examined in detail later in the text.

4.1.4 Are Fuel Treatments Effective?

Fuel treatments are a complex and divisive topic for wildfire suppression researchers and practitioners. The effectiveness and uses of fuel treatments have been examined extensively in the literature (Reinhardt et al. 2008, Amiro et al. 2001, Agee et al. 2000). Some research suggests that the application of fuel treatments can help mitigate wildland fire costs (Wei et al. 2008, Stephens et al. 2012), while other research suggests the link between them is weak (Carey and Schumann 2003). Reinhardt et al. (2008) further notes that there is significant complexity when analyzing the effectiveness of fuel treatments. As a case study, the fuel treatments associated with the Funny River fire in the Kenai National Wildlife Refuge in 2014 were shown to significantly reduce the spread and, potentially, costs of the fire (Saperstein et al. 2014). However, the cost effectiveness of fuel treatments across the entire Alaskan landscape should be analyzed in the aggregate. If there are no identifiable cost savings from fuel treatments on a large scale, other tactics should be pursued to combat the predicted increase in wildfire frequency and severity. If certain fuel treatments in certain locations reduce suppression expenditures, then those treatments should be prioritized over less effective resource usage. The larger applicability of the Alaskan model may be informative for other sparsely populated areas bordering open wildlands.

4.2 Data

4.2.1 State of Alaska Wildfire Suppression Data

The primary expenditure and wildfire characteristics data for this analysis was obtained from two sources; The Alaska Fire Service - Alaska Interagency Coordination Center (Alaska Fire Service – Alaska Interagency Coordination Center 2019) for the general wildfire information and the Alaska Department of Natural Resources who provided suppression cost information (Direct Correspondence). This data was provided from accounting spreadsheets with line items expenditures for individual fires. This data was then coded for type and aggregated to get totals. Other data sources include the United States Geological Survey for topographical data, the Kenai Peninsula and Fairbanks North Star Boroughs for fuel treatment data, and the Western Regional Climate Center, and National Oceanic and Atmospheric Administration for climate variables. This data was analyzed in ESRI ArcMap, and open-source GIS software (QGIS 2019). Other variables were generated spatially and used the aforementioned software. Variable definitions and descriptive statistics for all data used in the analysis can be found in table 4.2. Our data set only includes large wildfires, which was self-defined as wildfires 50 acres and larger. The data also includes fires from all four protection zones.

The spatial data was compiled using shape files, as well as input by hand using coordinate projections. Using spatial coordinates provided in the fire data, ignition cites were plotted for each wildfire[2]. These points were then analyzed to apply variable values from other data sources. For example, interactions and distances to fuel treatments were calculated in ArcMap and QGIS by measuring the

[2] The use of ignition point analysis is supported by findings in Hand et al. (2016) that a more robust spatially descriptive model was not necessarily a better predictive model across their entire sample.

distance from ignition points to the nearest fuel treatment. This process was also used with the climate data (precipitation, temperature, RH). The nearest weather station was determined for each wildfire, and weather data for the discovery month was pulled and added to the data set. In the event data was not available from the nearest weather station, the next closest weather station data was used until suitable data was found[3]. Raster data was used to determine the approximate elevation at each wildfire. An elevation raster was drawn, and elevation data was extracted at each fire point. The same process was used to estimate values for slope, aspect, and fuel type. Aspect data was used to create a binary variable for south facing, by attributing a 1 value to aspects between 90° and 270°, and a 0 for all others.

The *totalcost* variable includes all suppression costs associated with the fire. It is the sum of the individual costs of overhead and hand crews, engine costs, aviation costs, equipment and supply costs, as well as any repayment to federal agencies suppressing wildfires on state lands. These costs include type 1-4 hand crews, smokejumpers, incident command managers, air tanker drops, helitack runs, aviation fuel, retardant, engine time, dozers, pumps, as well as administrative costs and miscellaneous fees. Because these total expenditures are DOF-centric, much of the later analysis is based on looking only at DOF fires to ensure the maximum completeness of fire costs. The initial data set used for this analysis includes 280 wildland fires of greater than 50 acres across eight years (2007-2015) for which the State of Alaska staffed and incurred suppression costs. These wildfires include fires ignited in state (DOF) and federal (AFS/USFS) lands. Pre-negotiated agreements between the State of Alaska and Federal government agencies ensure for compensatory cross payments when their respective resources are used.

4.2.2 Data Descriptive Statistics

Descriptive statistics of our data set shows that 2010 and 2015 had the largest total state expenditures for wildfires ($40,216,231 and $49,265,893 respectively in 2015 dollars[4]) (Table 4.3). These years also had large areas burned on state lands. For fires in our data set, 2010 saw 770,033 acres burned and 885,661 in 2015. The only year that had more acreage burned in this time frame was in 2009, where over two million acres were burned (2,127,051). The probabilistic nature of wildfire, along with changing climatic variables can create very different fire conditions from year to year which introduces significant variability into a relatively small data set. As an example, 2015 had total expenditures almost 25 times than of 2008. Figure 4.4 shows how the inflation adjusted total costs and acres burned change over time in our dataset wildfires. Figure 4.5 illustrates the same data, but from a per-acre perspective.

[3] This process is inherently problematic in Alaska, as we cannot be guaranteed that multiple weather stations are available near all wildfires. The accuracy of the ignition site climate data is reduced the further away the data was collected. Incident reports (IC-209) were not complete enough to use as a reliable weather and climate data source.
[4] The Urban Alaska Consumer Price Index (CPI) for all goods for all urban consumers was used to calculate inflationary changes, using 2015 as the base year.

We caution making long-term inferences about any trends because of the limited time frame over which the data are observed. Table 4.4 shows total acres and costs for all wildfires in the data set broken down by protection level. The cost per acre is significantly different between protection zones and is positively correlated to level of suppression response.

Other descriptive statistics of variable data are also shown in Table 4.2. Most of the wildfires in the data set fall into the limited and full protection zones. The dominant fuel type at the site of ignition was most often spruce, with mixed forests a distant second. The largest fire in terms of acreage was the Minto Flats fire in 2009, at over half a million acres. The most destructive in terms of structures threatened and burned was the Caribou hills fire in 2007. The most expensive wildfire in real 2015 dollars was the Hasting fire at over $22 million. Approximately 85% of these wildfires were caused by lightning, with percentage of human caused fires increasing with management zone. A frequency table of wildfire cause by protection zone can be seen in table 4.5 and shows significant correlation between the two (χ^2 test p value = 0.03).

4.3 Model

4.3.1 Endogeneity of Wildfire Costs

When modelling wildfire costs, explanatory variables may be affected by reverse causality (otherwise known as endogeneity). Wildfire costs are often modeled with total burn area, or total active days as explanatory variables. This presents a problem, since the burned area from a wildfire, and active fire days should be directly correlated to how many suppression resources are ordered (and thus affecting total cost). Estimating the effect of area burned and active days on total costs without acknowledging this endogeneity would result in biased parameter estimates. One common method to deal with this problem is the use of an instrumental variable (IV) via a two-stage least squares (2SLS) regression. There are examples of wildfire costs being modeled with this approach to resolve our endogeneity problem (Hand et al. 2016, Donovan et al. 2011, Gebert and Black 2012, Lankoande & Yoder 2006). Strictly speaking, the use of 2SLS does not remove bias, but IV estimators are asymptotically unbiased, making them consistent estimators. Our sample size of 163 DOF fires gives us enough sample size to benefit from this unbiasedness. The potential endogenous variables will be tested for explicitly to test for the bias in the dataset.

4.3.2 Instrumental Variables

While acres burned and active days are the most likely candidates for endogenous variables, instrumental variables also need to be identified to inform the 2SLS model. In order to defend the choice of instrumental variable, we need to assume both instrument exogeneity and relevance. We begin with our generic structural equation (Eqn. 1), where Y is our dependent variable (costs), X is our matrix of explanatory variables, and u is our random error term.

$$\boldsymbol{Y} = \beta_0 + \beta_1 \boldsymbol{X} + u \qquad \text{[Eqn. 1]}$$

Instrument exogeneity and relevance are met if and only if the following equations are true:

$$Cov = (z, u) = 0 \text{ [Instrument Exogeneity]}$$

$$Cov = (z, x) \neq 0 \text{ [Instrument Relevance]}$$

where u is our random error of our structural cost equation, z is our instrumental variable, and x is an endogenous variable in **X**.

While seen as a statistical property, our instrument exogeneity condition is discussed from an economic or physical perspective, and not a statistical one. One potential instrumental variable unique to Alaskan wildfires is *lightning.* Once ignited, there should be no physical differences between wildfire that is caused by human or natural means ceteris paribus. Suppression resources are ordered under primary considerations of protecting human lives and property. Conversely, if we consider a simple regression (Eqn. 2) of *x* on our instrument *lightning* (z), we can test the statistical significance of the $\widehat{\beta_1}$ on the estimated regression. Finding statistical significance at a certain acceptable level allows us to reject the null hypothesis of $\beta_1 = 0$, and show that the instrument relevance assumption has been met. This is done as a test for weak instruments in our analysis. If we assume that *acres* is a suitable endogenous variable[5], then there is also evidence of a correlative relationship between lightning strike caused wildfires and acres burned. In the US, wildfires caused by lightning burned up to nine times larger areas than those that were human causes from 2008-2012 (Ahrens 2013). This is also intuitive when viewed from the Alaskan landscape. The large area of the state increases the number of probabilistic lightning strikes and subsequent wildfires. These fires are often very far away from any population centers and are often only monitored instead of suppressed. This would then lead to a positive correlation between lightning caused wildfire and total wildfire acres burned. We can again see this explicitly by looking at table 4.5 which shows a highly significant correlation between these two variables ($\chi^2 p$ value <0.001).

$$x = \beta_0 + \beta_1 lightning + v \qquad \text{[Eqn. 2]}$$

[5] The rest of this section will assume that acres is the one and only endogenous variable used in our model. Wu-Hausman testing will determine the actual variables used as endogenous variables.

Another potential choice for instrument is based on two of the previous studies looking at wildfire expenditures (Donovan et al. 2011, Gebert and Black 2012). These studies found that the year a wildfire took place could be a suitable instrumental variable. After controlling for climate and weather considerations, there should be no differences between real expenditures based merely on the passing of another year. Again, we can approach our instrument relevance via instrument strength tests to determine the best choices for instrumental variables.

4.3.3 Structural Model

A discussion of the model begins with a general economic function defining the variables responsible for changes in costs (Eqn. 3).

$$cost = f(area, topography, climate, fuels, fuel\ treatments, year\ variables, u) \quad \text{[Eqn. 3]}$$

Again, area (*acres)* should be thought of as an endogenous control, as area burned should be directly correlated to cost spent on the fire ceteris paribus. This economic equation leads to our reduced two-stage structural equation which estimates costs by first estimating exogenous variables. Using the natural log transformation allows us to discuss our parameter estimates in percentage terms. The first stage of our 2SLS model begins with estimating the endogenous variable (Eqn. 4).

$$\begin{aligned} lnacres = {} & \beta_0 + \beta_1 lndays + \beta_2 strthreat + \beta_3 modified + \beta_4 full + \beta_5 critical + \beta_6 lnslope + \\ & \beta_7 facesouth + \beta_8 lnelev + \beta_9 tundra + \beta_{10} mixed + \beta_{11} spruce + \beta_{12} FT_{5km} + \beta_{13} temp + \\ & \beta_{14} precip + \beta_{14} RH_t + \beta_{14} RT_{t-1} + \beta_{15} lightning + \beta_{16} 2007 + \beta_{17} y2008 + \beta_{18} y2009 + \\ & \beta_{19} y2010 + \beta_{20} 2y011 + \beta_{21} y2012 + \beta_{22} y2013 + \beta_{23} y2014 + u \qquad \text{[Eqn. 4]} \end{aligned}$$

Based on the choice of binary predictors, our base scenario is a human caused, north facing wildfire in a limited suppression zone igniting shrub fuels in 2015 that is not 5km from a fuel treatment. This information is only useful when interpreting the parameter estimates of our binary control variables. Once parameters have been estimated, it uses the predicted values for *lnacres* into the second equation (note the use of the fitted value in equation 5). Remember, that any instrumental variables must not be included into this second stage, or we are violating our instrument endogeneity. Based on our previous arguments, we will test for *lightning* and our year dummies as instrumental variables. This would then lead to our structural equation (Eqn. 5).

$$\begin{aligned} lntotal = {} & \beta_0 + \beta_1 \widehat{lnacres} + \beta_2 lndays + \beta_3 strthreat + \beta_4 modified + \beta_5 full + \beta_6 critical + \\ & \beta_7 lnslope + \beta_8 facesouth + \beta_9 lnelev + \beta_{10} tundra + \beta_{11} mixed + \beta_{12} spruce + \beta_{13} FT_{5km} + \\ & \beta_{14} temp + \beta_{15} precip + \beta_{16} RH_t + \beta_{17} RT_{t-1} + u \qquad \text{[Eqn. 5]} \end{aligned}$$

Please note that all the computational analysis for this model was done using R studio and various community packages (R Core Team 2018, RStudio Team 2016). The AER package was used for IV-2SLS regression estimates and diagnostic tests (Kleiber and Zeileis 2008).

4.4 Results

4.4.1 Endogenous and Instrumental Variables

Through the model specification process, testing was done to identify appropriate endogenous and instrumental variables. Using *acres* and *days* as candidates for our endogenous variables, and *lightning* and our year binary variables as candidates for instruments, we have nine possible combinations to test. Table 4.6 shows gives us the results three distinct tests: A weak instrument statistic, the Wu-Hausman endogeneity test, and the Sargan over-identification test. The weak instrument statistic is a test our instrument relevance condition. Specifically, it is an F-test of the instrument(s) in the first stage of our regression. While weak instruments may still have some non-zero correlation with the endogenous variable(s), it risks giving us asymptotically biased estimators. Rejecting the null hypothesis suggests that the correlation between endogenous and instrumental variable is large enough to avoid this issue. The Wu-Hausman tests the consistency between OLS and IV estimates. If the two estimates are consistent, it suggests that there is little need for the endogenous variable to be estimated in a first stage, and that is not a suitable choice for endogeneity based on the data. The null hypothesis in this case is that there is consistency between the two estimators. Finally, the Sargan test checks for over-identification of our instrumental variables. If we use more instruments than necessary, this test checks for correlation with the structural error (u). If correlation is found, it indicates that at least one of the instruments used is exogenous, and inappropriate to use.

The endogeneity of *days* is the most straightforward to discuss. Both on its own and when paired with *acres, days* passes the Wu-Hausman test and suggests that it is an appropriate choice for an endogenous variable. The endogeneity of *acres* is less clear. While it never passes the Wu-Hausman test by itself, it comes close when choosing the right IV (*year*). Strictly speaking, there is little statistical evidence that acres is endogenous with costs. However, the logical arguments for the endogeneity of *acres* still exist. There is also significant correlation between *acres* and *days* both intuitively and numerically *(*cor (*acres, days)* =0.52), suggesting that it could still perform well as an endogenous variable based on the results of *days*. When paired together, both *acres* and *days* were found to be endogenous. However, this is most likely due to the significance of *days,* and not their joint significance.

The instrumental variables candidates were *lightning* and *year*. Because we have identified appropriate endogenous variables, the next step will be to find a suitable instrument for those variables.

The weak ID statistic shows us that while *lightning* was a strong instrument for *acres*[6], it was a weak IV for *days* (as well as both *acres* and *days*). The *year* variable performed similarly, with one notable exception. When both *acres* and *days* are considered endogenous, *year* is a strong IV. When both *lightning* and *year* are used for IVs for *acres* and *days,* we no lose our strong IV for days. The Sargan test for over-identification found that when *year* or both *year* and *lightning* were used on *acres*, at least one of the year binaries, and/or *lightning* may be better suited as an exogenous control variable, and not an IV. We select two of the models based on the outcome of this preliminary testing:

Model 1: Endogenous variables *acres* and *days*; Instrumental variables *year.*

Model 2: Endogenous variable *days*; Instrumental variables *year.*

While our IV specification for using *days* alone was weak, it is important to remember that using both *acres* and *days* as endogenous variables passed the Wu-Hausman test despite *acres*, not because of its significance. We present the results of both models to identify any differences from our endogeneity and IV choices.

4.4.2 Selected Model Results

Parameter estimates for both models can be seen in table 4.6. Out of the 18 structural model variables, only 6 showed statistical significance in model 1. These included *lnacres*, *full*, *critical*, *spruce*, *lnprecip* and *lnRH_1*. The variable *lnacres* had a positive coefficient, indicating that as a wildfire's burned acreage increases by 1%, the cost of that fire increases by 0.67%. The binary variables for suppression management zones were mostly significant, with fires in both critical and full zones increasing costs significantly (243% and 217% respectively). Wildfires ignited in spruce forests were more likely to cost more than our base scenario by 139%. For every 1% increase in total monthly precipitation in the month the wildfire ignited, the costs were reduced by 0.59%. Similarly, with relative humidity, when average RH of the month before the ignition month increases by 1%, wildfire costs are reduced by 2.19%. Model 2 has similar outcomes, with the biggest change being the addition of *lightning* as significant, suggesting that wildfires ignited by humans were 102% more expensive that lightning caused fires[7]. This is an intuitive result and supported by the correlation between lightning caused wildfire and protection zone. It should also be noted that *lightning* was almost significant at the 10% level in model 1, with a p value of 0.105. Many of other control variables were not significant, but more importantly, neither was *FT_5KM.* The fuel

[6] This further supports the evidence found in Ahrens (2013) that lightning strikes are positively correlated with total area burned.
[7] The baseline result for the *lightning* variable was a human caused fire.

treatment binary variable did not show any statistical significance in either model, suggesting that having a fuel treatment within 5 km of the wildfire ignition point did not affect total costs.

Variance Inflation Factor analysis was done to examine the levels of multicollinearity and can be seen in table 4.7. While multicollinearity does not make estimators biased in a technical sense, it does inflate standard errors (and reduces *p* values), so an examination of excessive correlation may shed light on borderline significant parameter estimates. Model 1 had the least amount of problematic multicollinearity. Relative humidity and its 1-month time lag both high levels of multicollinearity, presumably from each other (cov (RH, RH_1) =0.849). These values are just above the threshold of 5, indicating that both estimates may be incorrectly reported as significant. This is particularly pertinent for RH_1, as it is significant just above the 5% level. The variable *lndays* had a very high VIF, again indicating that any significance may be unreliable. Luckily (or not), this variable's estimates had no statistical significance, so any reduction in standard error did not change our interpretation of that variable. Model 2 saw the exact same issues as Model 1, with the inclusion of *lnacres* as a new problematic variable. In this case, we did find statistical significance at the 1% level (*p* value: 0.004). The strength of significance here may assuage fears of multicollinearity causing concern, but it is still a real possibility given the magnitude of the VIF. One last thing to consider while there may be multicollinearity issues present in these models, there was not a large VIF for our FT variable. Because most of the other variables of note are control variables, their issues with multicollinearity does not affect our estimates for the primary variable of interest.

4.5 Discussion

4.5.1 Model Estimators

Large wildfires burning in Alaska have a wide variety of characteristics, each affecting the suppression costs associated with them. While over 160 Alaskan wildfires were analyzed, only a small fraction had a chance to have any interaction with fuel treatments. There was no statistically significant relationship between fuel treatments and total wildfire suppression costs that was identified. While this should not suggest the complete ineffectiveness of fuel treatments, it does indicate that suppression costs of the fires in the dataset were not influenced by fuel treatments in the aggregate. This may be because some Alaskan fuel treatments could not stop advancing wildfire on their own (Little et al. 2018), or because there is such a small chance for a fire to interact with a fuel treatment. This makes studies of fuel treatments inherently problematic for many WUI communities in the US. The case study of the funny river fire posited that the fuel treatments bordering the Kenai National Wildlife Refuge saved homes, expense, and left "hundreds of other structures" unscathed (Sapperstein et al 2014). There is also the probabilistic component of this analysis, in that given the size of the state, there may not be enough wildfires that had any interactions with fuel treatments to accurately assess their cost effectiveness. It is also possible that wildfire has not attacked many cost-effective fuel treatments that have been constructed to protect vulnerable communities.

The suppression management areas provide interesting insight into how these wildfire costs change. While there was no significant difference between expenditures in limited and modified fires, there were very significant differences for the other two. The magnitude of these changes even reflected the level of response, as wildfires in critical zones were the most expensive and those in full zones were less expensive. These results are also supported by the initial wildfire statistics showing a positive correlation between cost per acre and suppression zone (Table 4.4). This has an intuitive explanation, as these zones are defined by the imperativeness of a suppression response. Because of the overriding paradigm of protecting life and property, this result gives overall reliability to the model, and these variables as controls. The fuel type at ignition site also is intuitive, as mixed and spruce forests are more likely to burn hotter and faster than shrubs or tundra due to the significant difference in fuels loads. Precipitation and our lagged RH variable are also in line with intuition, as more moisture, both during the fire and moisture of the fuel load both reduced costs significantly. Even with the significance, and intuitive nature of the RH predictor, we cannot ignore our VIF findings that potentially invalidate this relationship. Finally, human caused fires are more expensive than those caused by lightning. This can be explained intuitively by the fact that human caused fires are more likely to start in areas closer to population centers, increasing the suppression response in both time and effort. This can also be seen in the positive correlation between lightning caused fired in limited and modified zones (0.308 and 0.047 respectively) and the negative correlation in full and critical zones (-0.119 and -0.635 respectively)[8]. The predictors are almost identical for model 2, so this discussion applied to that model as well. Control variables that were not significant included terrain characteristics (slope, aspect and elevation), temperature, and total structures threatened. While the control variables we chose had legitimate ecological reasoning behind them, they weren't significant indicators in our dataset. Like our fuel treatment argument, there is no reason to believe that these aren't good control variables, just that they weren't econometrically shown to be significant in this instance.

4.5.2 Endogeneity and Instrumental Variables

The use of endogeneity and instrumental variables was critical to the estimation in our models. While the results were described when a model was specified, a more critical look is required. From one

[8] The VIF for *lightning* was less than two, which suggests these correlations do not affect our parameter estimates.

perspective, both *acres* and *days* showed significance as endogenous predictors. When paired together they had statistically significant testing results. There is also a strong economic argument for their endogeneity, as increased suppression resources should decrease both acres burned and total active days. However, one could also make the argument that neither were very clear and strong candidates for endogeneity. Not only did *acres* show no evidence for endogeneity on its own, it was only included in our model when paired with *days*. Even *days* wasn't immune to this, as it didn't always pass the Wu-Hausman test when checking multiple instruments. We see a similar pattern when looking at the two instruments used in the analysis. *Lightning* was a poor instrument when used by itself, except when paired with *acres* as the endogenous variable. *Year* was much stronger but was still seen as a weak instrument when paired with the best choice for endogenous variable, *days*. For both the endogenous and IV conversation, there is little that stands out as a clear result. However, the best choices individually for these variables, are *days* and *year*, with the best producing model using both endogenous variables paired with *years*. Ultimately, the predictors are similar for each model, but the validity of the instrumental and endogenous variables will be useful for future studies.

4.6 Conclusion

Wildfires in the state of Alaska are unique in many ways. They can often burn huge areas of land while keeping risk to human life and property very low. But there are also large WUI portions of the state that require investigation into the best way to provide support to their communities. Fuel treatments are often discussed as a means to provide that protection, but this needs to be done in the lens of social effectiveness, which includes cost-effectiveness. The overall effectiveness of fuel treatments was not empirically found in large wildfires in Alaska from 2007-2015 in this analysis. The main drivers of costs were found in the suppression management zones, with other weather and ecological control considerations. Instrumental variables were identified, along with useful endogeneity of model variables. There are still some unanswered questions when it comes to explaining expenditure data of large Alaskan wildfires. Further research into this topic may help illuminate just how effective fuel treatments can be in a social context. For example, wildfires in critical suppression zones were the most expensive ceteris paribus. Examining the overall effectiveness of fuel treatments in critical zones may provide better insight that a statewide aggregate model.

It is important to note that in the context of the analysis presented is econometric in nature. It reflects the current landscape of Alaskan fuel treatments as they were between 2007 and 2015. There is a myriad of reasons why a fuel treatment may not be leveraged to ultimately reduce costs that could range from incident commander decisions, to wind direction or other stochastic justifications. This discussion also doesn't include suppression efficiencies from these fuel treatments themselves. Suppose a wildfire would cost the same with or without a nearby fuel treatment, but with one present, it reduced the risk to spreading closer to populated communities. In this scenario, fuel treatments would still be categorized as providing a social benefit even without a budgetary one. For Alaskan wildfire risk mitigation, the use of fuel treatments is popular. Continued and ongoing research will need to keep pace with the changing landscape to continue to provide protection for all Alaskan residents.

4.7 References

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Table 4.1: Wildfire counts and acres burned from 1990-2018 by protection zone. Time trend statistical significance (ß time) is also shown. Maximum values for this time series are in bold. Data on acres burned by protection area were not available before 2003. *, ** and *** correspond to statistical significance at the 10%, 5%, and 1% levels respectively.

	Statewide						State Lands Only (DOF)	
Year	#	Acres	Critical	Full	Modified	Limited	#	Acres
1990	802	3,189,427	-	-	-	-	460	981,291
1991	760	1,750,653	-	-	-	-	493	174,277
1992	474	135,360	-	-	-	-	332	36,667
1993	**869**	713,117	-	-	-	-	535	120,223
1994	643	265,722	-	-	-	-	446	90,827
1995	421	43,946	-	-	-	-	327	16,585
1996	724	599,267	-	-	-	-	565	81,737
1997	773	2,026,899	-	-	-	-	**612**	1,058,911
1998	412	120,752	-	-	-	-	338	63,708
1999	486	1,005,248	-	-	-	-	333	145,806
2000	369	756,296	-	-	-	-	260	35,197
2001	321	98,720	-	-	-	-	297	87,127
2002	543	2,183,363	-	-	-	-	399	802,517
2003	476	602,718	-	-	-	-	357	11,481
2004	696	**6,523,182**	**135,826**	723,281	220,835	**5,038,956**	392	**2,102,067**
2005	624	4,663,880	709	253,796	**831,330**	3,578,045	346	720,806
2006	307	266,268	1,102	607	148,629	115,929	249	170,942
2007	509	649,411	85	73,552	7,904	567,870	284	135,976
2008	367	103,649	395	3,647	2,327	97,280	254	8,529
2009	527	2,951,593	1,426	50,498	213,902	2,685,766	330	1,142,995
2010	688	1,125,419	18,492	296,109	140,903	669,914	330	268,818
2011	515	293,018	2,038	80,332	6,886	203,761	356	145,839
2012	416	286,888	2,832	26,035	14,737	243,283	269	26,598
2013	613	1,316,289	2,277	29,715	56,100	1,225,196	452	589,123
2014	393	233,530	588	63,459	16,980	152,502	304	201,998
2015	768	5,111,453	26,087	**963,484**	763,034	3,358,847	479	1,045,564
2016	572	500,949	1,210	49,370	67,638	382,162	375	104,627
2017	362	653,148	161	57,041	2,002	593,843	177	81,247
2018	362	411,177	178	32,107	41,741	337,134	203	46,036
TOTAL	15,792	38,581,343	193,406	2,703,033	2,534,948	19,250,488	10,554	10,497,518
ß (time)	-7.00*	5,481	-3,077	-8,384	-14,328	-148,232	-6.25***	899

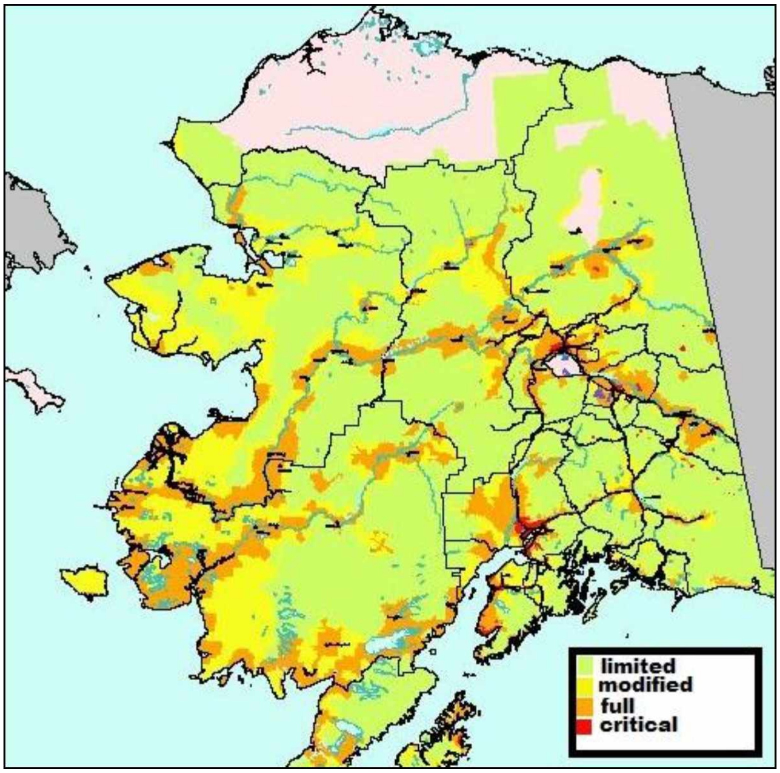

Figure 4.1: Map of Alaskan suppression response zones based on the Alaska Interagency Fire Management Plan 2010 (Alaska Department of Natural Resources: Division of Forestry 2019a).

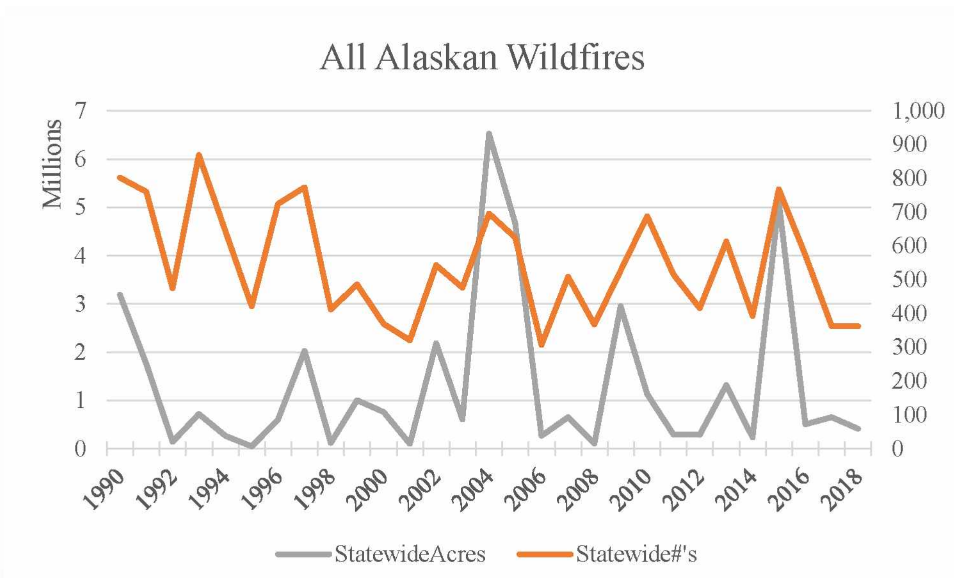

Figure 4.2: Total number and acres of all wildfires in the State of Alaska by year from 1990-2018. Acres in on the primary (left) axis and number of wildfires in on the secondary (right) axis.

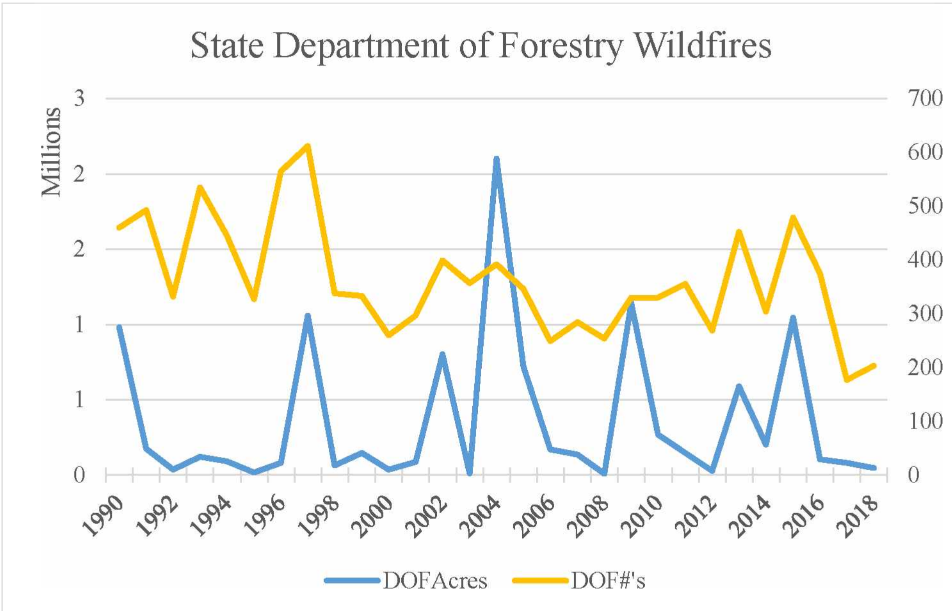

Figure 4.3: Total number and acres of Alaska Department of Forestry wildfires by year from 1990-2018. Acres in on the primary (left) axis and number of wildfires in on the secondary (right) axis.

Table 4.2: Descriptive statistics and definitions for data set variables. Sum/Count column sums data for continuous variables or counts data for binary variables. Statistics for year binary variables are presented in a different table. Mean and StdDev columns gives average values and standard deviation values for dataset variables respectively. Max and Min columns give us the largest and smallest values of data set variables.

Variable	Definition	Sum/Count	Mean	StdDev	Max	Min
totalcost	total state expenditures	$213,943,538	$764,084	$2,176,119	$22,814,501	$84
acres	total acres burned	4,626,895	16,525	48,249	517,078	50
days	total active days wildfire burned	14,256	51	40	204	0
str_threat	Structures threatened by wildfire	4,732	17	154	1,603	0
modified	binary variable indicating fire started in a modified suppression management zone	29	0	0	1	0
full	binary variable indicating fire started in a full suppression management zone	117	0	0	1	0
critical	binary variable indicating fire started in a critical suppression management zone	18	0	0	1	0
limited	binary variable indicating fire started in a modified limited management zone	116	0	0	1	0
slope	slope at ignition point	526	2	2	14	0
facesouth	binary variable indicating an aspect between 90° and 270°	133	0	1	1	0
elev	elevation at ignition point	75,103	268	218	999	1
tundra	binary variable indicating that the primary fuel type region at the ignition point was arctic tundra	42	0	0	1	0
mixed	binary variable indicating that the primary fuel type region at the ignition point was mixed forest	75	0	0	1	0
spruce	binary variable indicating that the primary fuel type region at the ignition point was spruce forest	126	0	0	1	0
shrub	binary variable indicating that the primary fuel type region at the ignition point was shrub	37	0	0	1	0
FT_5km	binary variable indicating a fuel treatment was within 5 km of wildfire ignition point	9	0	0	1	0
temp	average monthly temperature at ignition point	15,506	55	7	67	15
precip	sum of monthly precipitation at ignition point	415	1	1	11	0
RH	relative humidity at ignition point	17,067	61	12	89	1
RH_1	relative humidity of previous month at ignition point	16,226	58	13	97	0
lightning	binary variable that indicates the fire cause being lightning	231	1	0	1	0
y20XX	Binary variable for each year in the dataset (2007-2015)	-	-	-	-	-

Table 4.3: Yearly breakdown of costs and acres burned in total and per fire in the dataset. Costs are inflation adjusted to 2015 dollars. Included wildfires are those larger than 50 acres.

year	fires	real costs ($2015)	acres	cost/fire	acres/fire
2007	44	$14,937,615	438,053	$339,491.25	9,956
2008	25	$1,995,310	62,549	$79,812.40	2,502
2009	53	$30,718,600	2,127,051	$579,596.23	40,133
2010	72	$40,216,231	770,033	$558,558.77	10,695
2011	9	$37,273,694	82,751	$4,141,521.53	9,195
2012	9	$10,487,538	28,316	$1,165,281.96	3,146
2013	16	$16,714,011	31,345	$1,044,625.68	1,959
2014	3	$12,334,646	201,138	$4,111,548.76	67,046
2015	49	$49,265,893	885,661	$1,005,426.38	18,075

Table 4.4: Wildfire acreage and cost statistics by protection zone. Includes cost per acre values by protection zone.

	Total Acres	Total Cost	Total Cost/Acre
Limited	2,781,013	$19,802,186	$7.12
modified	259,662	$11,335,447	$43.65
full	1,491,595	$153,412,784	$102.85
critical	94,626	$29,393,121	$310.63

Table 4.5: Frequency table of wildfire cause by protection zone. Significant correlation was found between the two variables (χ^2 test p value = 0.0001). Included percentage of cause by protection zone.

	Lightning	Human	Total
limited	111 (95.7%)	5 (4.3%)	116 (100%)
modified	23 (79.3%)	6 (20.7%)	29 (100%)
full	87 (75.7%)	28 (24.3%)	115 (100%)
critical	13 (72.2%)	5 (27.8%)	18 (100%)

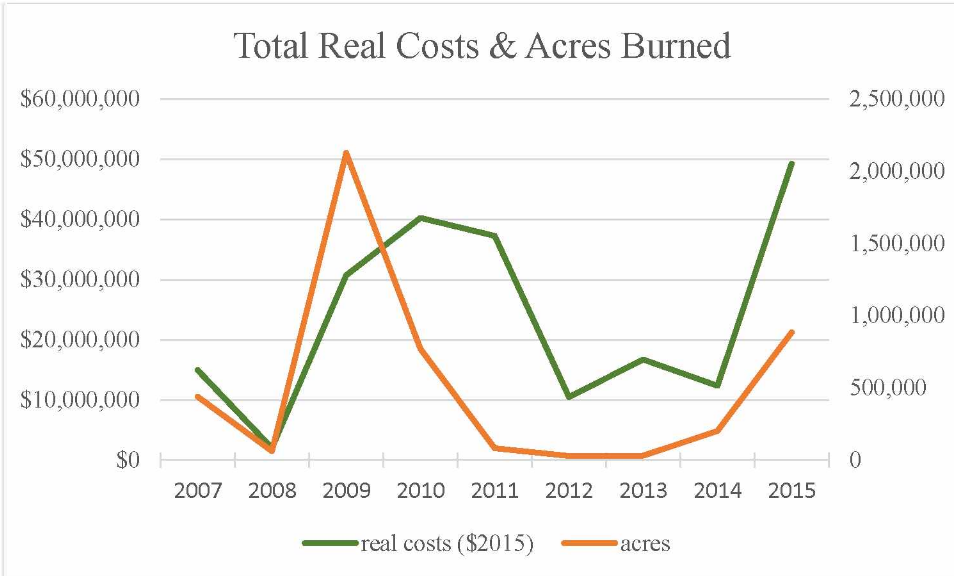

Figure 4.4: Total real costs and acres burned per year for wildfires used in the dataset. Costs are inflation adjusted to 2015 dollars. Real costs are plotted on the primary (left) axis and acres on the secondary (right) axis.

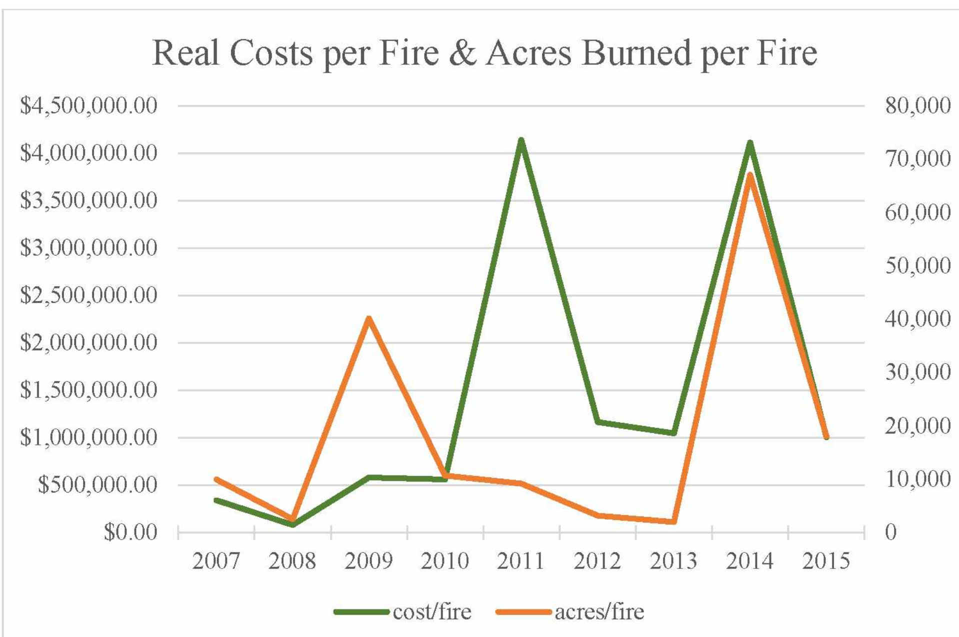

Figure 4.5: Total real costs per fire and acres burned per fire per year for wildfires used in the dataset. Costs are inflation adjusted to 2015 dollars. Real costs per acre are plotted on the primary (left) axis and acres per fire on the secondary (right) axis.

Table 4.6: Parameter estimates for two specified models. *, ** and *** correspond to statistical significance at the 10%, 5%, and 1% levels respectively. R^2 values are not reported as they do not have the same interpretation as a standards OLS regression.

	(1)	**(2)**
Endogenous Variable(s)	*lndays, lnacres*	*lndays*
Instrumental Variable	*years*	*years*
(Intercept)	-0.941	-1.071
	(6.70)	(6.438)
lndays	-0.976	-0.973
	(0.921)	(0.918)
lnacres	0.667**	0.681***
	(0.313)	(0.246)
str_threat	0.001	0.001
	(0.001)	(0.001)
modified	0.846	0.847
	(0.978)	(0.977)
full	2.169***	2.176***
	(0.462)	(0.453)
critical	2.428**	2.457***
	(0.992)	(0.905)
lnslope	0.101	0.101
	(0.140)	(0.140)
faceSouth	0.486	0.485
	(0.444)	(0.443)
lnelev	0.054	0.050
	(0.254)	(0.248)
tundra	0.480	0.465
	(0.957)	(0.933)
mixed	1.174	1.166
	(0.729)	(0.720)
spruce	1.393*	1.381*
	(0.776)	(0.759)
FT_5km	0.809	0.779
	(1.176)	(1.097)
lntemp	2.779	2.789
	(1.842)	(1.836)
lnprecip	-0.593*	-0.594*
	(0.342)	(0.341)
lnRH	1.682	1.691
	(1.134)	(1.127)
lnRH_1	-2.185*	-2.190*
	(1.115)	(1.112)
lightning	-0.989	-1.002*
	(0.606)	(0.579)
N	163	163
Wald Test (*P* value)	0.000***	0.000***
Weak ID (days)	0.092*	0.276
Weak ID (acres)	0.001***	N/A
Wu-Hausman	0.010***	0.002***
Sargan	0.3680	0.480

Table 4.7: Variance Inflation Factors (VIF) for all variables in both models. VIF values larger than 5 are in bold and indicate a significant amount of collinearity.

	(1)	(2)
Endogenous Variable(s)	*lndays, lnacres*	*lndays*
Instrumental Variable	*years*	*years*
lnacres	4.11	**8.84**
lndays	**8.29**	**13.81**
str_threat	1.46	1.26
modified	1.15	1.15
full	1.56	1.5
critical	2.11	1.76
lnslope	2.09	2.09
face	1.42	1.42
lnelev	3.23	3.09
tundra	3.91	3.72
mixed	3.10	3.03
spruce	4.32	4.14
FT_5km	1.89	1.64
lntemp	3.56	3.54
lnprecip	4.23	4.21
lnRH	**5.36**	**5.30**
lnRH_1	**5.82**	**5.80**
lightning	1.95	1.79

Chapter 5 Conclusion

The work discussed in this dissertation covers a range of topics relating to wildfire. The unique perspectives of Alaskan Homeowners were investigated, and significant results for their preferences were identified. These results can potentially be applied to similar communities that have comparable challenges, such as having significant WUI communities in northern latitudes with plenty of open wildlands. Homeowner incentives are important to understand, as sound policy and budgetary decisions can be informed by these incentives. Understanding the economic tradeoffs associated with fuel treatments can better maximize the use of pre-suppression funds. The aggregate efficiencies of previous decisions should be assessed to proficiently allocate future public spending.

Chapter 2 and 3 offer significant insight into the preferences and behavior of homeowners. Chapter 2 showed no discernable differences between residents of the two different boroughs in the way they responded to the survey portion. While residents of the Fairbanks North Star Borough (FNSB) had larger defensible spaces, there were no other differences of note between the issues these homeowners faced. Both boroughs shared problems with misidentification of objective wildfire risk and a lack of proper compliance with best wildfire protection practices. These results support the idea that this is endemic of WUI locations in general, as these results match other studies (Brenkert-Smith et al. 2013). There were large numbers of homeowners doing some mitigation actions on their property, but less were in general compliance with Firewise. Besides the misidentification of wildfire risk, amenity and privacy values were of particular importance. This was seen in both the preference for thinned fuel breaks, as well as directly stated by survey respondents (with the loss of these values as a disincentive to reduce fuels). Free riding wasn't seen in these responses, as homeowners tended to take similar actions as their neighbors did.

Chapter 3 provided quantitative willingness-to-pay (WTP) estimates for those who completed the choice experiment. In general, respondents favored a moderate number of neighbors mitigating their property. This is due to the perception that reducing fuels to the maximum extent in a portion of the community would negatively change the amenity values around the homeowner's property. Thinned fuel treatments had a large WTP associated with it. No treatment on public lands was generally more preferred than clear cutting to create fuel breaks. This implies that homeowners would rather transfer the cost onto themselves to avoid the risk reduction from clear cutting on public lands. There was evidence of altruistic and free riding choices being made, but free riding choices still tended to at least match neighbors' risk as well, indicating restrained free riding. In general, those who felt they were in a higher risk area had higher

WTP estimates across all variables. The same is said for those that had some direct experience with wildfire.

The results of this work have important policy and institutional implications. The aggregate cost effectiveness of fuel treatments has been called into question. From an individual level, there is a strong preference for the most expensive type of fuel treatments. This is also combined with a WTP that may be able to offset these costs. While none currently exists, a payment mechanism can be created to move this cost on to those who most directly benefit. Future studies can be developed, such as a referendum style choice experiment to determine the preferences for these mechanisms in different Alaskan communities. The lack of objective wildfire risk information is contrasted with its clear benefits and should offer motivation for capacity building programs like Firewise, especially given that they are shown to increase homeowner participation (Sturtevant & McCaffrey 2006). The gap in subjective and objective risk seen should encourage these programs to increase effort, especially in those communities where this discrepancy is the largest. Fuel treatments should not be thought of as unfeasible. The success of the Funny River fuel treatment had measurable impacts on the reduction in spending, property damage, and vulnerability of those affected homeowners. However, there should be critical thought put into the placement and use of fuel treatments moving forward. A thorough analysis of what made the funny river fuel treatment (and other effective fuel treatments) so effective should be done to influence future spending decisions. If the effectiveness is driven by the more probabilistic elements of wildfire (wind speed, relative humidity, temperature, etc.) then it may be more difficult to depend on the effectiveness of any fuel treatments.

Future studies, especially with follow up surveys would be valuable to study both the longitudinal differences in Alaskan WUI resident attitudes, as well as to study the effects of individual fire seasons and evacuations. By having these groups respond to the survey again, we can test for any statistically significant changes in responses and observe how these external changes affect homeowner preferences and behavior. As with a survey of this length, there remains a source of information that has yet to be analyzed. The work here focuses on the major themes currently faced by wildfire practitioners and researchers. Some of these themes could be analyzed even further by including other survey information. For example, the insurance portion of both chapter 2 and 3 could be more informed by including home values. While this data was not immediately available, the survey asked questions on property and home sizes in terms of both square footage and acreage. These metrics can act as proxy variables for home value to better inform WTP and correlations between insurance and subjective homeowner wildfire risk. Subjective homeowner feelings of protection and safety is another possible area of investigation. Questions were asked about fire protection agents, and how far away they are. Objective measurements to the nearest fire department and the specific fire department agency (federal, state, municipal, volunteer or none) can be made when comparing respondents to their spatial data. This could be another "Objective vs Subjective" type of analysis to investigate the levels of informed decision-making being done by homeowners. Questions were also asked about previous participation in programs designed to increase wildfire knowledge and information sharing. This could create another category to see how WTP changes for those with and without experience in these programs. In this data set, there was a low number of respondents who had any experience with these programs (N = 94) with most of them having no Firewise or state stewardship program experience. This could then be turned into a program effectiveness analysis, examining how these respondents answered subjective questions as a measurement of community wildfire knowledge.

Potential extensions of this research are also numerous. A more complete picture of the economic impact from wildfires is much larger in scope than the work presented here. Private and state considerations were the focus of the econometric analysis, but federal expenditures were explicitly excluded in the cost models. There are other significant direct, indirect, and induced impacts from wildfire that were not examined, such as changes to tourism, employment, recreational values, and local spending. The impacts from wildfire smoke and pollution are also associated with increased respiratory related disease and increased medical costs. Fine particulate matter pollution ($PM_{2.5}$ and PM_{10}) already impacts the Fairbanks North Star Borough with "spare the air" days and air quality index advisories to stay indoors. Lastly, it is also worth investigating the economic impacts that wildfires have on atmospheric and climate-based variables, such as lighting and precipitation.

There is a critical need to continue investigating Alaskan wildfire from an economic, budgetary, and policy perspective. Wildfires will continue to increase in severity and frequency and will impact generations to come. Understanding homeowner preferences to fuel treatments, neighborhood involvement and how their WTP reflect these changes is critical to future policy decisions. This work acts as a primer for continued discussion and research into these topics. The implications of this work reach beyond Alaskan borders, as many of these results have been seen elsewhere in the US. This essential work is currently threatened by economic and political forces affecting research and institutional budgets across the state. Wildfire researchers and practitioners must continue their endeavors to keep studying the vulnerable populations of the state. The stakes are high, so we must continue to investigate these important issues that continue to impact the lives and livelihoods of those who continue to move "North to the Future".

5.1 References

Sturtevant, V., & McCaffrey, S. (2006). Encouraging wildland fire preparedness: Lessons learned from three wildfire education programs. *The public and wildland fire management: Social science findings for managers*, 125-136

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Appendix

IRB Approval Form

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Institutional Review Board

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April 30, 2018

To:	Joseph Little, PhD Principal Investigator
From:	University of Alaska Fairbanks IRB
Re:	[918057-8] EPSCoR Wildfire Mitigation Preferences Survey

Thank you for submitting the Amendment/Modification referenced below. The submission was handled by Exempt Review. The Office of Research Integrity has determined that the proposed research qualifies for exemption from the requirements of 45 CFR 46. This exemption does not waive the researchers' responsibility to adhere to basic ethical principles for the responsible conduct of research and discipline specific professional standards.

Title:	EPSCoR Wildfire Mitigation Preferences Survey
Received:	April 30, 2018
Exemption Category:	2
Effective Date:	April 30, 2018

This action is included on the May 30, 2018 IRB Agenda.

Prior to making substantive changes to the scope of research, research tools, or personnel involved on the project, please contact the Office of Research Integrity to determine whether or not additional review is required. Additional review is not required for small editorial changes to improve the clarity or readability of the research tools or other documents.

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