THE EFFECT OF WILDFIRES, SPRUCE BARK BEETLES, AND PRESCRIBED BURNS ON RESIDENTIAL PROPERTY VALUES IN ALASKA'S KENAI PENINSULA

By

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A Thesis Submitted in Partial Fulfillment of the Requirements

for the Degree of

Master of Science

in

Resource and Applied Economics

University of Alaska Fairbanks

August 2019

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Abstract

This study estimates the effect that forest fires, spruce bark beetle outbreaks, and controlled burns performed by fire management agencies have on nearby residential property values. Using the hedonic pricing framework, and ten years of house sales from south-central Alaska's Kenai Peninsula, this study found little evidence that wildfires and spruce beetle outbreaks have a significant effect on the final sale price of surrounding homes, but found that the controlled burns contribute to a decrease in surrounding home values. As Alaska's climate becomes warmer and drier, these disturbances threaten to increase in frequency and severity. Understanding how homeowners perceive fire risk and forest damage is increasingly important to fire management policy, as the behavior of residents can help limit both the cost from and incidence of wildfires. The study's findings suggest that homeowners are either insulated from, or indifferent to fire risk, but targeted burns of high-risk areas by fire managers could increase awareness and sensitivity to fire risk.

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Introduction

In the last fifty years, rising temperatures have resulted in a drier, more wooded Alaska. This has left Alaska increasingly vulnerable to forest fires and spruce bark beetle infestation (Klein, Berg, and Dial 2005). Since 1990 spruce bark beetles (*Dendroctonus rufipennis*) have resulted in the deaths of nearly 5 million acres of forest in Southcentral Alaska's Kenai Peninsula. These dead trees are left dried and standing, which results in both increased ignition risk and burn severity, as fires that typically stay in the underbrush are now more likely to reach the canopy (Hess, Cullen, Iñiguez, et al. 2019). As temperatures rise, spruce bark beetles are able to move to higher latitudes, and in 2018 they reached Anchorage resulting in 1,500 acres lost, up from only 18 lost the previous year (United States Forest Service 2018). As their range expands, so does the importance of understanding how residents perceive beetle outbreaks; public engagement with the issue can aid detection and limit its spread.

Hansen and Naughton (2013) estimated the effect of fires and spruce bark beetle damage on property values in the Kenai Peninsula. They used a panel of houses that were assessed in 2001 and 2010 for property tax adjustment. The Kenai Peninsula Borough evaluated these estimates to be 92% of the actual sale value in 2006, up to 94.5% in 2010. Hansen argues that this measurement bias certainly contributes to error, but does not necessarily mean that the error is systematically related to any of the independent variables. This study used the point of origin of 1199 wildfires, defined as large fires if they exceeded 3.3ha burned, and divided their relationship to each house into three distance bands: 0.0-0.1km, 0.1-0.5km, and 0.5-1.0km away from the property center. Beetle outbreaks were described using the same distance band, but no division based on the size of the outbreak was used. Hansen and Naughton (2013) found that small wildfires close to a home are associated with a decrease in property values (-5.5%), but large wildfires close to a home are associated with an increase in values (+18.6%). They proposed that large fires might result in positive aesthetic attributes, such as better views of more open grassy areas, and might cause homeowners to underestimate their future fire risk. Beetle damage saw moderate increases in property values in the outer two distance bands, which adds further evidence that homeowners might value the defoliation both provide.

Prescribed burns are an important tool land managers have at their disposal to reduce hazardous fuel loads, such as the buildup of standing deadwood from a beetle infestation, that are threatening developed areas. Public opinion on the use of controlled burns is divided. Some see them as wasteful of natural resources and unnecessarily dangerous, while others find the alternative of mechanical removal to be a poor excuse to allow logging on public lands (Brunson and Evans 2005). Brunson and Evans (2005) found that public opinion remained split between these two options, even after a prescribed burn escaped control in Utah at the end of the 2003 fire season; the week of smoke and $3 million spent extinguishing the blaze appeared instead to reduce trust in the managing agencies. The risk of escapes persists due to surprises in fuel condition, fire behavior, changes in weather conditions, and from breakdowns in communication between agencies and nearby landowners (Dether 2005). The need for controlled burns remains, as they allow land managers to undo years of buildup that occurred under policies of strict suppression, and they allow them to do so on a large scale in areas of limited access (such as the 41,000 acre Alphabet Hills prescribed burn in Southcentral Alaska) (Woodford 2006).

Building off Hansen and Naughton (2013), this paper estimates the economic impact of fires, both planned and unplanned, and beetle outbreaks as reflected in residential property values using the hedonic pricing framework. It determines if these ecological disturbances vary in economic effect based on size and distance from the property center, and if they have a synergistic effect. To control for spatial interactions from neighboring homes and exogenous factors, I use a spatial autoregressive model with autoregressive disturbances. Unlike similar research in the region (Hansen and Naughton 2013), this study uses confidential sale prices instead of publicly available property tax assessments, takes into account the synergistic effect of beetle damage on fires, and tests if homeowners react differently to controlled burns than they do to wildfires.

Analytical Framework

Hedonic pricing, as popularized by Rosen (1974), treats goods as a bundle of characteristics that can be valued individually. Market prices for the good reflect the equilibrium between alternative combinations of characteristics found in competing products or services. Rosen proposed that the hedonic framework could be best used to find the equilibrium between supply and demand functions, not the functions themselves, in the absence of information about consumer and producer preferences and constraints. When applied to the housing market, these characteristics follow the general form:

$$\text{House Price} = f(E,G,D) \tag{1}$$

where E contains environmental factors such as nearby wildfire activity, G contains geographic features such as distance to the coastline or elevation, and D contains dwelling specific features such as interior area or lot size which are anticipated to influence housing prices (Rosen 1974).

Spatial econometric techniques gained popularity as they control and describe the interdependence present within the housing market (Pace, Barry, and Sirmans 1998). The price of a house is dependent on the characteristics and relative location of neighboring houses. This spatial autoregressive process is analogous to those found in time series analysis. Unlike temporal autoregression, where expected results depend on previous time periods, but past results cannot depend on future results, spatial autoregression is bi-directional. Changes in the price of house 'A' result in changes in neighboring house 'B', and then the resultant change in 'B' in turn affects 'A'. Ignoring spatial effects in hedonic house pricing produces biased OLS estimates (Tse 2002). In the context of the housing market, positive autoregression (also called spatial autocorrelation) means that the increase in price of house 'A' is expected to result in a secondary increase in the price of house 'B'.

Measures of the strength of spatial autoregression such as the Moran's I correlation coefficient (Moran 1950) or Anselin's (1995) local indicator of spatial association (LISA) depend on the specified spatial weights, which in turn must be justified by the hypothesized spatial relationship. These spatial weights are stored in a *nxn* matrix, *W*, where *n* is the number of observations. By convention, an observation has no initial spatial effect on itself (Anselin 2003), so values along the diagonal are zero. The most common weighting schemes are based on contiguity, where the matrix would be filled with '1's for adjacent neighbors and '0's for all others, or inverse distance, where values would be filled with (distance between observation i and j)$^{-1}$. These techniques have been adapted to social and economic relationships which do not need to depend on geographic location, such as social networks and trade networks (Biles 2003).

These weights are used within the regression to create spatial lag and spatial error terms. They are typically standardized by row or spectrally. Row standardization divides each value, w_{ij}, by the sum of all values within its row [w_{i1}+w_{i2}+…w_{ij}]. Each row will then sum to 1, and the resultant matrix can be loosely interpreted as a spatially weighted average. It is important to note that after this transformation w_{ij} does not need to, and rarely does, equal w_{ji}. Intuitively this means that the effect that house 'A' has on house 'B' does not need to be equivalent. For example, if house 'A' is relatively isolated on the outskirts of town, it's nearest neighbor 'B' could depend more on house 'C' and 'D' in the town center which are closer to it than 'A' is to 'B'. Spectral standardization divides each value w_{ij} by the maximum eigenvalue, which ensures that the matrix is non-singular and that the spatial error coefficient is consistent and asymptotically efficient (Kelejian and Prucha 1998). Prucha contends that the choice to row standardize instead of using spectral standardization must be backed up with theoretical justification. Non-symmetrical effects, ease of interpretation, and reasonable indifference to number of neighbors make row standardization a popular choice in spatial hedonic house pricing models (Hansen and Naughton 2013, Liao and Wang 2012).

Study Area and Data Sources

As of July 2018, the Kenai Peninsula is home to an estimated 58,533 people, with a per capita income of $33,336 in 2017 dollars (United States Census Bureau 2018). From 2005 to 2015, Kenai Peninsula's population grew 1.2% per year, on average (Anchorage Economic Development Corporation 2017). Kenai Peninsula Borough contains 31,250 housing units (United States Census Bureau 2018), with the largest population centers clustered around the western coastline. Eastern and southern Kenai Peninsula are dominated by Kenai Fjords National Park and Kachemak Bay state park, with limited development along the coast and along corridors through the Kenai Mountain Range.

Alaska does not require the public disclosure of final-house-sale prices. I obtained privileged final-prices and corresponding housing characteristics through the Alaska Multiple Listing Service. The sample was limited to 3,748 private, single-family houses sold between 2006 and 2016 in the Kenai Peninsula Borough, Alaska. Houses within incorporated city limits were excluded, as they fall into critical protection areas which receive high priority responses that realistically insulate them from fire risk. Houses that had no neighboring houses sold in the same year within 5km were excluded. These isolated observations would have no spatial error or spatial lag coefficient. The loss of these two degrees of freedom from a portion of the sample would invalidate estimation and tests (Anselin and Bera 1998).

I standardized sale prices to 2017 prices using the All-Transactions House Price Index for Kenai Peninsula Borough compiled by the St. Louis Federal Reserve (2018). This index is built directly off of regional mortgage information. I used this index instead of CPI or GDP deflator to better account for the local economic disturbances. The economy of the Kenai Borough is primarily composed of oil and gas, fishing, timber, tourism, and healthcare sectors. A more general index would understate the impact of changes in local production or employment, and could require the addition of local economic variables to the model. As the research questions center more around spatial and ecological effects than temporal and economic effects, this alternative was unappealing.

Historical fire information was obtained from the Alaska Fire Service and the Alaska Interagency Coordination Center (2018). Size and point-based location information for 1,333 fires from the 2001 to 2016 fire season was used to generate circular polygons of the final burn size. Perimeters for only 33 of the largest fires were available through the AICC, so this approximation serves to establish an area threatened by each fire. Thirty-seven of these fires were designated as controlled burns by fire managers.

Information about historical spruce beetle damage was obtained from the United States Forest Service Insect and Disease Detection Survey's annual summary maps (United States Forest Service 2018). These maps are obtained through aerial surveys, in combination with ground surveying. Not all aerial observations can be verified from the ground each year, but the persistent nature of beetle outbreaks and their resultant damage lessens the impact of this logistical issue. Both fire and beetle damage have lasting effects, so information was collected for five years before each sale. This short timeframe should capture the period most obvious damage and early post-fire successional changes to the forest, but not complete regrowth (Klein, Berg, and Dial 2005).

Dummy variables for wildfires and beetle damage indicate the closest distance band around each observation intersected by the fire or beetle damage polygons. The dummy variable for prescribed burns makes no distinction for the size or distance of the burn to the property, as this is already captured by the six fire dummies.

Kenai Peninsula Borough's Geographic Information Systems Database provided city limit, road, and water information shapefiles (Kenai Peninsula Borough 2018), and elevation information came from the United States Geological Survey's 1/3 arc second digital elevation model (United States Geological Survey 2018). I calculated all distances in ArcGIS Pro 2.3 software, with distances calculated from each property's center point.

Town dummy variables for closest incorporated town use the town of Kenai, AK as a baseline. Similarly, 2006 is omitted from the time dummy variables. The dry cabin dummy variable defines a dry cabin as a house with no bathrooms, which usually indicates the presence of an outhouse. The variable 'remodeled' has no limitation on the recency of renovations, which could be a problem for older houses in the sample, but in the absence of more consistent information about the quality or condition of the homes, it will have to do.

Table 1: Descriptive Statistics

	Mean	Std. Dev.	Min	Max	Data Source
Ln(Price)	12.1616	0.6227	9.1121	14.1617	AK MLS 2016
Ln(Home Square Feet)	7.2994	0.5531	4.7875	9.1893	AK MLS 2016
Ln(Lot Square Feet)	11.1271	0.8724	6.0767	15.7253	AK MLS 2016
Bedrooms	2.6732	1.1198	0	10	AK MLS 2016
Bathrooms	1.8347	0.9129	0	13	AK MLS 2016
Age of Home	18.4381	12.5913	0	112	AK MLS 2016
Dry Cabin	0.0547	0.2274	0	1	AK MLS 2016
Remodeled	0.2604	0.4389	0	1	AK MLS 2016
Garage	0.6518	0.4765	0	1	AK MLS 2016
Fire Service Area	0.6926	0.4615	0	1	AK MLS 2016
Ln(Distance to coastline)	8.3812	1.2652	0.0000	10.5260	KPB 2018
Ln(Distance to Inland Water)	5.9923	1.0928	-0.1799	8.1305	KPB 2018
Ln(Distance to Nearest City)	8.3497	1.4757	1.3491	11.3585	KPB 2018
Ln(Distance to Primary Road)	3.6488	1.4191	-6.0253	10.4172	KPB 2018
Ln(Elevation)	3.9781	0.7607	0.8760	7.1008	USGS 2018
Homer	0.2065	0.4049	0	1	AK MLS 2016
Kachemak	0.0688	0.2532	0	1	AK MLS 2016
Seldovia	0.0040	0.0631	0	1	AK MLS 2016
Seward	0.0507	0.2194	0	1	AK MLS 2016
Soldotna	0.4717	0.4993	0	1	AK MLS 2016
Small Wildfire 0.0km-0.1km	0.0075	0.0861	0	1	AICC 2018
Large Wildfire 0.0km-0.1km	0.1593	0.3660	0	1	AICC 2018
Small Wildfire 0.1km-0.5km	0.1222	0.3276	0	1	AICC 2018
Large Wildfire 0.1km-0.5km	0.1630	0.3694	0	1	AICC 2018
Small Wildfire 0.5km-1.0km	0.2999	0.4583	0	1	AICC 2018
Large Wildfire 0.5km-1.0km	0.1708	0.3763	0	1	AICC 2018
SBB Damage 0.0km-0.1km	0.0275	0.1635	0	1	USFS 2017
SBB Damage 0.1km-0.5km	0.0683	0.2523	0	1	USFS 2017
SBB Damage 0.5km-1.0km	0.1233	0.3288	0	1	USFS 2017
Wildfire and SBB Both Present	0.0427	0.2022	0	1	AICC&USFS
Prescribed Burn	0.0021	0.0462	0	1	AICC 2018

Methodology

I estimated multiple generalized spatial two stage least squares regressions (GS2SLS) of the form[1]:

$$y = \rho Wy + \beta X + c + u$$

$$u = \lambda Wu + \epsilon \tag{2}$$

where y is the natural log of real property values, ρ is spatial lag coefficient, W is the spatial weights matrix, βX contains all exogenous variables and their coefficients, c is all the pooled cross section time constants, and λ is the spatial error coefficient (Drukker, Prucha, and Raciborski 2013). Wy is the spatially weighted average of nearby properties for each house. However, ρ cannot be accurately interpreted as the percentage change per percent increase of average neighboring property value. In OLS ρ and λ are both set to zero. In the spatial lag model λ equals zero. In the spatial error model ρ is equal to zero. The spatial mixed model or SARAR(1,1) model allows both spatial constants to vary, as both nearby houses and spatially dependent innovations are expected.

I created local inverse distance weights, with observations more than 5km away having no direct spatial effect. Larger distances have limited justification for being included. This cutoff band limits interaction to places that realistically share similar amenities not included in the model such as school district, recreational access, and natural beauty. Even with this local limit in place, houses further away still influence each other, only this time indirectly through the chain of influence that each neighbor has on subsequent neighbors between the two houses that

[1] All spatial weights and regression results were created in StataIC 15 (64 bit) using the *spmatrix* and *spregress* commands.

are further than 5km away. Spatial dependence is limited to houses sold within a year of each observation. This means that the matrix contains 10 years of differing spatial weights. Allowing the weights to change over time is consistent with our goals of observing the effects of environmental changes. The importance of which is seen in the indirect effects of wildfire occurrence. Information about the position of nearby fires does not fully account for the location of and damages from the resultant decrease in air quality. Previous studies have modeled the cost decreased air quality through the hedonic house pricing framework (Bayer, Keohane, and Timmins 2009), so in the absence of consistent air quality observations throughout the study area and timeframe, it is reasonable to assume that some amount of this effect is captured by the spatial error term. This unaccounted-for effect changes over time with the intensity of the fire season, or even from pollution originating in Asia, so it is appropriate to allow the weights to do the same.

To create spatial weights that take into account the time of each house sale I first created a regular distance-banded spatial weights matrix, D. Then I created a nxn time matrix, T, where $T_{ij}=1$ if house i and j were sold in the same year and zero if they weren't. Entry-wise multiplication (also known as a Hadamard product) of D and T eliminated any houses from differing time periods from influencing each other. The resultant matrix, W, was then row standardized.

D_{ij} = (Euclidean distance between observation i and j)$^{-1}$

T_{ij} = 1 if house i and j were sold in the same year, 0 if they weren't

$W_{ij} = D_{ij}T_{ij}$

$$W = D \circ T \tag{3}$$

As the exact structure of the underlying spatial relationship is unknown, I used models of increasing specification, starting with OLS, then spatial error and spatial lag, and finishing with the comprehensive spatial mixed model. Wald chi-squared test statistic will help determine the best of the 4 models.

Results

Wald chi-square test statistics suggest that the spatial mixed model is superior, so discussion of the results will focus on that model which is found in table 2. Interpretation of the mixed model is less intuitive than OLS regression. In the presences of positive coefficients for rho and lambda, interpreting coefficients as you would in OLS regression will understate the magnitude of the partial effect of each independent variable. A positive, statistically significant value of rho suggest that spillover effects are present. Calculating marginal effects in OLS requires the calculation of the partial derivative of the dependent variable, with respect to the independent variable. For linear coefficients this is just equal to the dependent variable's corresponding coefficient beta, with some minor adjustments required for log based functional forms. The spatial mixed model presents multiple difficulties.

$$y = \rho W y + \beta X + \mathrm{c} + \mathrm{u}$$
$$u = \lambda W u + \epsilon \tag{4}$$

The presence y on the right-hand side of the equation makes the model recursive in nature, which results in an expanding infinite series, with different expected coefficients for each observation, for each variable (Vega and Elhorst 2013).

$$\left[\frac{\partial E(y)}{\partial x_{1k}} \cdots \frac{\partial E(y)}{\partial x_{nk}}\right] = (I - \rho \mathrm{W})^{-1}\beta_k$$
$$(I - \rho \mathrm{W})^{-1} = I + \rho \mathrm{W} + \rho^2 W^{2+} \rho^3 W^3 + \cdots \tag{5}$$

For the local spatial effects present in this study, and more generally in the absence of strong justification, a truly global multiplier derived from the entirety of this series is not always appropriate (Vega and Elhorst 2013, Lesage 2008). Distributing β_k into the first two terms of the series results in the direct effect and the first order indirect effect. Multiplying the identity matrix, I, by β_k results in a n x n matrix with β_k along the diagonal and zeroes everywhere else, meaning this term contributes only to each observation's own the expected price. The next term, $\beta_k \rho W$, results in a *nxn* matrix with zeroes along its diagonal, meaning this term only contributes to neighboring properties.

The spatial mixed model produced a small statistically significant value for both ρ and λ. In a row standardized matrix, these constants range between -1 and 1. The resulting ρ of 0.185 means that higher order effects rapidly become negligible. This makes intuitive sense, as low housing density in the Kenai Peninsula could limit their transmission.

Fire service area and SBB outbreaks 0.1-0.5km away had a statistically significant positive effect on expected property values, while prescribed burns had a significant negative effect. Table 2 lists the complete results, while table 3 provides an interpretation of significant coefficients. While the first order direct effect is the same at each observation, it is important to note that the indirect effect at varies significantly between each observation, depending on the number and location of neighbors.

House characteristics were all significant and rational. For example, a 1% increase in interior size increases the expected home value by 0.419% and each additional year a house ages is expected to decrease the sale price by 1.10%. Unsurprisingly running water, indoor plumbing, and a garage commanded a premium value in frigid Alaska. Moving farther away from water and towns also decreased expected home value. The year dummy variables (base year 2006) saw a significant increase starting in 2013, which could indicate a slow recovery from the great recession.

Few environmental variables were statistically significant. This is partially surprising, as previous research (Hansen and Naughton 2013) had found strong evidence that small fires negatively impacted expected home values, but large fires raised expected values. This differing result could be due to homeowners and homebuyers valuing these events differently than property tax accessors. It also could be due to complex opinions about the amenities and disamenities provided by the occurrence of a fire. For example, a fire could clear brush and allow for a better view, or the composition of a post-fire forest could be preferable ascetically. It could also be due to difficulty accessing future fire risk. The resulting landscape could be an eyesore, but there might be perceived value in getting seemingly inevitable fire over with.

Most surprising was the sharp decrease in expected home value that resulted from being near a prescribed burn. A prescribed burn less than one kilometer from a house is expected to decrease sale price by 12.45%. The most appealing explanation for this result is that homeowners are forced to come to terms with the risk that they are living in. A prescribed burn near a house would mean land managers have decided that area is very high risk, or it could be a planned fire misbehaving and straying closer to residential areas than intended. Either option would leave a lasting impression on the homeowner. The magnitude of the decrease suggests there might be something else at play here. It might be worth focusing in on a smaller number of prescribed fires where something might stand out easier in future studies.

Table 2: Regression Results

VARIABLES	OLS	Spatial Lag	Spatial Error	Spatial Mixed
Ln(Home sqft)	0.432***	0.420***	0.421***	0.419***
	(0.0249)	(0.0246)	(0.0245)	(0.0246)
Ln(Lot sqft)	0.0763***	0.0786***	0.0865***	0.0837***
	(0.00945)	(0.00930)	(0.00939)	(0.00938)
Bedrooms	0.00533	0.00854	0.00947	0.0104
	(0.0102)	(0.0101)	(0.0101)	(0.0101)
Bathrooms	0.128***	0.124***	0.119***	0.121***
	(0.0144)	(0.0142)	(0.0143)	(0.0143)
Age of Home	-0.0111***	-0.0109***	-0.0112***	-0.0110***
	(0.000629)	(0.000620)	(0.000625)	(0.000622)
Dry Cabin	-0.318***	-0.317***	-0.345***	-0.335***
	(0.0447)	(0.0434)	(0.0429)	(0.0430)
Remodeled	0.0984***	0.0988***	0.0987***	0.0998***
	(0.0132)	(0.0129)	(0.0127)	(0.0128)
Garage	0.245***	0.242***	0.244***	0.244***
	(0.0156)	(0.0154)	(0.0153)	(0.0153)
Fire Service Area	0.0433***	0.0403***	0.0444***	0.0413***
	(0.0149)	(0.0147)	(0.0145)	(0.0146)
Ln(Dist. to Coast)	-0.0210**	-0.0214**	-0.0222**	-0.0216**
	(0.00957)	(0.00922)	(0.0103)	(0.00963)
Ln(Dist. to Inland Water)	-0.0897***	-0.0854***	-0.0888***	-0.0855***
	(0.00690)	(0.00683)	(0.00719)	(0.00698)
Ln(Dist. to Nearest City)	-0.0415***	-0.0275***	-0.0380***	-0.0257***
	(0.00513)	(0.00562)	(0.00629)	(0.00617)
Ln(Dist to Primary Road)	-0.000759	-0.000118	-0.000926	-0.000442
	(0.00496)	(0.00478)	(0.00465)	(0.00469)
Ln(Elevation)	0.0550***	0.0347**	0.0306**	0.0243*
	(0.0132)	(0.0136)	(0.0156)	(0.0147)
y2007	0.0182	0.0258	0.0180	0.0263
	(0.0253)	(0.0247)	(0.0338)	(0.0281)
y2008	0.0207	0.0339	0.0194	0.0350
	(0.0259)	(0.0260)	(0.0350)	(0.0297)
y2009	0.0321	0.0355	0.0339	0.0369
	(0.0282)	(0.0279)	(0.0376)	(0.0317)
y2010	0.0198	0.0284	0.0141	0.0273
	(0.0321)	(0.0317)	(0.0424)	(0.0359)
y2011	0.0333	0.0338	0.0325	0.0338
	(0.0293)	(0.0288)	(0.0394)	(0.0329)
y2012	0.0538*	0.0492*	0.0477	0.0470
	(0.0289)	(0.0285)	(0.0390)	(0.0325)
y2013	0.0725***	0.0683***	0.0765**	0.0700**
	(0.0254)	(0.0252)	(0.0338)	(0.0286)
y2014	0.105***	0.0952***	0.0966**	0.0924***
	(0.0296)	(0.0291)	(0.0380)	(0.0325)
y2015	0.0923***	0.0927***	0.0919**	0.0936***
	(0.0298)	(0.0292)	(0.0384)	(0.0328)
y2016	0.0486	0.0542	0.0456	0.0547
	(0.0346)	(0.0335)	(0.0449)	(0.0377)
Homer	-0.0282	0.0121	-0.0193	0.0202
	(0.0292)	(0.0295)	(0.0359)	(0.0324)
Kachemak	-0.0469	-0.0271	-0.0641	-0.0308

	(0.0337)	(0.0330)	(0.0421)	(0.0368)
Seldovia	-0.0739	0.0232	-0.0495	0.0436
	(0.140)	(0.144)	(0.204)	(0.172)
Seward	0.185***	0.164***	0.193***	0.167***
	(0.0356)	(0.0340)	(0.0451)	(0.0378)
Soldotna	0.0781***	0.0833***	0.0758***	0.0834***
	(0.0193)	(0.0188)	(0.0209)	(0.0196)
Small Wildfire 0.0km-0.1km	0.00105	0.00831	0.0149	0.0160
	(0.0648)	(0.0638)	(0.0628)	(0.0632)
Large Wildfire 0.0km-0.1km	0.192	0.163	0.189	0.161
	(0.128)	(0.120)	(0.122)	(0.118)
Small Wildfire 0.1km-0.5km	-0.0408*	-0.0388*	-0.0370*	-0.0377*
	(0.0222)	(0.0219)	(0.0221)	(0.0220)
Large Wildfire 0.1km-0.5km	-0.0633	-0.0414	-0.0458	-0.0354
	(0.143)	(0.135)	(0.139)	(0.134)
Small Wildfire 0.5km-1.0km	0.0497***	0.0369**	0.0301*	0.0290*
	(0.0164)	(0.0163)	(0.0170)	(0.0166)
Large Wildfire 0.5km-1.0km	-0.0555	-0.0543	-0.0541	-0.0541
	(0.0747)	(0.0710)	(0.0768)	(0.0725)
SBB Damage 0.0km-0.1km	-0.0273	-0.0348	-0.0239	-0.0327
	(0.0484)	(0.0484)	(0.0490)	(0.0490)
SBB Damage 0.1km-0.5km	0.100***	0.101***	0.0958**	0.0987***
	(0.0380)	(0.0371)	(0.0374)	(0.0371)
SBB Damage 0.5km-1.0km	-0.0285	-0.0317	-0.0240	-0.0299
	(0.0301)	(0.0290)	(0.0309)	(0.0296)
Wildfire & SBB Both Present	-0.0198	-0.00386	-0.0146	-0.00201
	(0.0389)	(0.0384)	(0.0412)	(0.0396)
Prescribed Burn	-0.118**	-0.137***	-0.113**	-0.133**
	(0.0513)	(0.0508)	(0.0565)	(0.0530)
Rho	-	0.176***	-	0.185***
	-	(0.0323)	-	(0.0337)
Lambda	-	-	0.301***	0.135***
	-	-	(0.0268)	(0.0422)
Constant	8.653***	6.507***	8.703***	6.378***
	(0.177)	(0.443)	(0.179)	(0.466)
R-Squared	0.6519	-	-	-
Pseudo R-Squared	-	0.6415	0.6347	0.6305
Wald χ2 test vs OLS	-	143.21	827.1	528.69
P-value	-	0	0	0
Wald χ2 test vs SL (2)	-	-	-	30.26
P-value	-	-	-	0
Wald χ2 test vs SE (3)	-	-	-	10.27
P-value	-	-	-	0.0014
Observations	3,748	3,748	3,748	3,748

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

Table 3: Direct and Indirect Disturbance Values

Variables	Direct Effect	Direct Effect Value at the Mean	Indirect Effect Value at the Mean
Small Wildfire 0.1km-0.5km	-3.700%	-$7,077.76	-$8,684.36
Small Wildfire 0.5km-1.0km	2.942%	$5,628.92	$6,906.66
SBB Damage 0.1km-0.5km	10.374%	$19,844.53	$24,349.12
Prescribed Burn	-12.453%	-$23,823.53	-$29,231.32

Mean House Price: $191,300

Direct Effect = $100[e^{B}-1]$

Spatial Multiplier = $1/(1-\rho) = 1/(1-0.185)$

Conclusion

Previous research (Hansen and Naughton 2013) found evidence that assessed property values were significantly impacted by nearby fire and beetle activity, with large fires seeing a counterintuitive increase in surrounding values. My analysis found little evidence to support those results, but uncovered a significant reduction in expected property values following a controlled burn by fire managers. The tradeoffs of using real sale prices instead of assessed are twofold: there were not enough repeat sales to create a panel dataset and sample size suffers as a result. In exchange we get a picture of how homeowners value these events, instead of how property tax assessors value, or think residents value, these events. The specification of spatial weights could have had a significant effect on our differing results and vastly different values for the spatial lag value rho (0.988 vs 0.185). A banded global Moran's I test of autocorrelation showed constantly increasing autocorrelation with increased search radius, with its most significant peaks in its otherwise steady rise at just over 5km. The clustering of both of out datasets centers around the western coastline, but both include some houses in the relatively unpopulated eastern mountainous part of the peninsula. Increasing the search radius results in somewhat suburban home near the city of Kenai being compared to houses about as far into the middle of nowhere as you can get. A high global autocorrelation in this context tells you "all the expensive houses are clustered by the coast where most of the economic activity is and the ones 50 miles from anything, that are all clustered in these mountains, they're pretty cheap", which could be better assessed through a car ride than a statistical analysis.

This study suggests that home sale prices are not terribly sensitive to these environmental disturbances. It is reasonable to expect some amount of exposure to forest fire throughout most of Alaska. Unlike other hedonic house pricing studies of pollution or crime, fires and SBB are not going to be worth moving away from for most people. It is also likely that homeowners misjudge the fire risk to their property, and are partially insulated from the consequences through homeowner’s insurance. The sharp drop following prescribed burns could be the result of improved awareness of risk. Perception of the risk might change from “it could happen anywhere in the state” to “fire managers decided out of all the places in this peninsula that my back yard needed to go”.

References

Alaska Department of Natural Resources and AK State Geo-Spatial Data Clearinghouse. (2018). *Physical Features Data*. Retrieved from http://www.asgdc.state.ak.us/#

Alaska Fire Service and Alaska Interagency Coordination Center. (2018). *Historical Fire Information*. Retrieved from https://fire.ak.blm.gov/incinfo/aklgfire.php

Anchorage Economic Development Corporation. (2017). *Economic Overview Kenai Peninsula Borough, Alaska.*

Anselin, L. (1995). Local Indicators of Spatial Association-LISA. *Geographical Analysis, 27*(2), 93-115.

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*.

Anselin, l., & Bera, A. (1998). *Spatial Dependence in linear Regression Models with an Introduction to Spatial Econometrics.*

Bayer, P., Keohane, N., & Timmins, C. (2009, 7). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management, 58*(1), 1-14.

Biles, J. (2003). *Using Spatial Econometric Techniques to Estimate Spatial Multipliers: An Assessment of Regional Economic Policy in Yucatán, Mexico *.*

Brunson, M., & Evans, J. (2005). Badly Burned? Effects of an Escaped Prescribed Burn on Social Acceptability of Wildland Fuels Treatments. *Journal of Forestry , 103*(3), 134-138.

Dether, D. (2005). *Prescribed Fire Lessons Learned Escape Prescribed Fire Reviews and Near Miss Incidents Initial Impression Report.* United States Forest Service.

Drukker, D., Prucha, I., & Raciborski, R. (2013). Maximum likelihood and generalized spatial two-stage least-squares estimators for a spatial-autoregressive model with spatial-autoregressive disturbances. *Stata Journal*.

Hansen, W., & Naughton, H. (2013). The effects of a spruce bark beetle outbreak and wildfires on property values in the wildland-urban interface of south-central Alaska, USA. *Ecological Economics*.

Hess, K., Cullen, C., Cobian-Iñiguez, J., Ramthun, J., Lenske, V., Magness, D., . . . Spruce, J. (2019, 2 1). Satellite-based assessment of grassland conversion and related fire disturbance in the Kenai Peninsula, Alaska. *Remote Sensing, 11*(3).

Kelejian, H., & Prucha, I. (1998). A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances. *Journal of Real Estate Finance and Economics*.

Kenai Peninsula Borough. (2018). *Geographical Information Systems Data Downloads*.

Klein, E., Berg, E., & Dial, R. (2005). Wetland drying and succession across the Kenai Penninsula Lowlands, south-central Alaska. *Canadian Journal of Forest Research, 35*(8), 1931-1941.

Lesage, J. (2008). An Introduction To Spatial Econometrics. *Revue D'Economie Industrielle*, 29.

Liao, W., & Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics*.

Moran, P. (1950). Notes on Continuous Stochastic Phenomena. *Biometrika, 37*(No. 1/2), 17-23.

Pace, R., Barry, R., & Sirmans, C. (1998). Spatial statistics and real estate. *Journal of Real Estate Finance and Economics, 17*(1), pp. 5-13.

Rosen, S. (1974, 1). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy, 82*(1), 34-55.

St. Louis Federal Reserve Bank. (2018). *All-Transactions House Price Index for Kenai Peninsula Borough*. Retrieved from https://fred.stlouisfed.org/series/ATNHPIUS02122A

Tse, R. (2002). Estimating Neighbourhood Effects in House Prices: Towards a New Hedonic Model Approach. *Urban Studies, 39*(7), 1165-1180.

United States Census Bureau. (2018). *QuickFacts: Kenai Peninsula Borough, Alaska*. Retrieved from https://www.census.gov/quickfacts/fact/table/kenaipeninsulaboroughalaska/PST045218

United States Forest Service. (2018). *Insect and Disease Detection Survey Annual Summary Maps*. Retrieved from https://www.fs.fed.us/foresthealth/applied-sciences/mapping-reporting/gis-spatial-analysis/detection-surveys.shtml

United States Geological Survey. (2018). *1/3 Arc Second Digital Elevation Model*. Retrieved from https://catalog.data.gov/dataset/national-elevation-dataset-ned-1-3-arc-second-downloadable-data-collection-national-geospatial

Vega, S., & Elhorst, J. (2013). *On spatial econometric models, spillover effects, and W*.

Woodford, R., & Alaska Department of Fish and Game. (2006). The Alphabet Hills Prescribed Burn.