Proceedings of the 5th International Fire Behavior and Fuels Conference
April 11-15, 2016, Portland, Oregon, USA
Published by the International Association of Wildland Fire, Missoula, Montana, USA

Spatially weighted hedonic property models for homes vulnerable to wildfire

David Rossi*
Department of Forest and Rangeland Stewardship, Colorado State University
Fort Collins, Colorado, USA
djrossi@rams.colostate.edu

Anne Byrne
Department of Agricultural and Resource Economics, Colorado State University
Fort Collins, Colorado, USA
anne.byrne@colostate.edu

Introduction

Scenic amenities near forested landscape represent an environmental amenity accruing to nearby landowners which competes with the dis-amenity of possibly damaging wildfire. This research seeks to determine how the implied value of aesthetic amenities compare to the dis-amenity of wildfire risk factors in Boulder County, Colorado. This can be accomplished by careful examination of the implicit relationship between nearby forest attributes and observed willingness-to-pay for residential land in a wildland-urban interface/intermix (WUI). A spatially weighted hedonic property model is used to glean insight into the preferences homebuyers have for (a) wildland-urban areas with moderate to high levels of vegetation density in their neighborhood and (b) a property's exposure to recent wildfire activity.

Hedonic modeling in the WUI

Several studies have previously analyzed the risk preferences of residential landowners in fire-prone communities using hedonic property models. In a case study analysis in Los Alomos, New Mexico, Loomis (2004) found that residential landowners rationally update their perception of a property's risk following wildfire events. Kim and Wells (2005) are the first to specifically estimate the implied value of medium forest canopy closure in a hedonic property study of residential transactions in Flagstaff, Arizona. Their results suggest that medium levels of vegetation in a community jointly benefit landowners through aesthetic values and reductions in wildfire risk compared to levels of high vegetation density. Donovan et al. (2007) use spatially weighted hedonic property models to determine if residential landowners capitalize wildfire risk information into land prices across a WUI region in Colorado Springs, Colorado. Their models find that the availability of risk maps have a significant impact on residential land prices in the community. Specifically, residential landowners in the WUI update their perceptions of risk in light of this new information by subsequently placing a lower premium on homes with hazardous building material and a higher premium on homes with more fire-resistant characteristics.

Comparing the aesthetic amenity from the dis-amenity of wildfire risk factors in a hedonic model

The research presented here builds on the work of Huggett et al. (2008) who use a least squares model for Chelan County, Washington to obtain separate estimators for both the marginal value of aesthetic amenities in the WUI and the negative impact of wildfire risk factors. They note the importance of not using a single neighborhood variable to estimate the negative amenity of wildfires because the proximity to elevated fire activity and risk factors is correlated with desirable scenic amenities in the WUI. Failure to include a separate estimator for aesthetic amenities may skew conclusions regarding homeowner perception of wildfire risk factors.

This research extends the analysis to a case study in Boulder County, Colorado and presents a spatially weighted model to compare the marginal impacts of scenic vegetation in the WUI and less nearby fire activity on percentage changes in sales prices. A spatially weighted hedonic model is used here to correct for biased and inefficient estimators that typically accompany a spatial dataset under four alternative definitions of nearest neighbors. The applied hedonic model that follows uses a cross-sectional term to capture the added aesthetic value of homes in communities with varying levels of neighborhood vegetation and housing density. Specifically, this study compares the relative changes in values for residential land in interface and intermix development regions. The model also attempts to separately capture the negative change in value from exposure to wildfire risk factors by including the impact of recent wildfire activity in the proximity around each residential land transaction.

Materials

Geo-coded data on residential housing transactions are available from the Boulder County assessor's office. These data contain structural attributes of each property sold between 2008 and 2014. Sales prices are deflated using the mean home price index for Boulder County in the year 2010. Point data on wildfire activity are available through the U.S. Geological Survey (wildfire.cr.usgs.gov/firehistory/about.html). Centroids from all wildfire activity occurring within 1.75 miles in the five years prior to each transaction are counted and joined to the housing transaction data.

The spatial classification of the WUI and vegetation characteristics are collected by the SILVIS Lab at the University of Wisconsin (silvis.forest.wisc.edu/maps/wui). All parcels in Boulder County are divided into areas of non-WUI development, 'interface' development, or 'intermix' development (Radeloff et al., 2005). These vegetation characteristics and housing density information from the U.S. census are used in the model to capture preferences for open space and scenic amenities in the hedonic model.

All environmental characteristics are joined and merged with the geo-coded transaction data in ArcMap 10.3.1. Spatially weighted regression models are fit using the 'spdep' package in the R statistical programming language (Bivand et al., 2013; Bivand and Piras, 2015). A sample of the population data frame is needed to estimate spatial models with the available computing power. Summary statistics for the sample of 5000 transactions in Boulder County from 2008-2014 are given in Table 1.

Table 1 – Summary Statistics on sample of housing transactions (2008-2014)

	Mean	Median	St. Dev.	N
Inflation adjusted Sales Price	$199,280	$159,141	158384.7	5000
Age of the structure	30.24 years	27.00 years	21.7475	5000
Total Finished Square Footage of the property	1663 sq. ft.	1453 sq. ft.	805.9997	5000
Number of Bedrooms	3.173	3.0000	1.1054	5000
Number of Bathrooms	2.642	3.000	1.0839	5000
Housing Density of neighborhood	1253.297 houses per sq. km	937.634 houses per sq. km	1204.176	5000
Count of Recent Wildfire Activity Within 1.75 miles	0.1212 wildfires	0.0000 wildfires	0.8337	5000
Number of non-WUI Transactions: 2936 Number of Interface Transactions: 1753 Number of Intermix Transactions: 311				

Methods

Failure to account for a spatial lag structure of the dependent variable could yield inefficient estimates of marginal impacts in a least squares regression (LeSage and Pace, 2009). Biased parameters may also arise from the omission of important neighborhood variables, but could also arise from the exclusion of positive externalities like the positive impacts of desirable characteristics of neighboring properties on any given property (LeSage and Pace, 2009). These two issues drive the motivation for a spatial Durbin model.

An application of a semi-log spatial Durbin model is used to estimate the hedonic price function:

$$\ln P_{it} = \rho \mathbf{W} \ln P_{it} + \mathbf{X}\beta + \mathbf{WX}\gamma + \varepsilon_{it}$$

The dependent variable ($\ln P_{it}$) represents the natural log of sales price at each location i in year t. $\mathbf{W}$ represents an NxN row-standardized weights matrix. Specifications are tested using 5, 10, 15, and 20 nearest neighbors to check for differing results under alternative definitions of neighbors to each observation. Use of the spatial Durbin specification allows for a spatial autoregressive term (ρ) to capture the spatial dependency of the dependent variable. This allows the model to capture the impact of nearby sales prices on the impact of any one sales price. The model also addresses any concern over biased estimators as a lag term on the independent variables

(γ) corrects any spatial dependence of model errors. A spatial lag of independent variables allows the structural and environmental characteristics of neighboring observations to influence the sales price for observation i. β represents a Kx1 vector of population parameters describing the direct impacts of a property's characteristics for which the applied model will obtain estimates. The NxK design matrix, **X**, contains the structural and neighborhood characteristics that are suspected to have an influence on sales prices. In this case, the independent variables are: age of the home, total finished square footage, number of bedrooms, number of bathrooms, housing density of the neighborhood, a cross-sectional term describing the vegetation density of the neighborhood, a trend variable (year), and the number of centroids from wildfire footprints that fall within 1.75 miles of a property 5 years prior to its transaction date.

Results

A common factor hypothesis test is conducted to determine if the estimated Spatial Durbin model with the lagged dependent and independent variables represents a significant improvement over a model which only captures the spatial error structure. Results of the Liklihood ratio tests and Wald tests indicate a Durbin specification better describes the data over a spatial error model and yields different estimates of impacts on land prices. Using alternative definitions of neighbors in the weights matrix (**W**) only slightly changes the parameter estimates. Estimates of impact on changes in sales price differ from those obtained using a least squares regression, but not drastically different from those obtained from spatial error models which do not capture the spatial dependency of the dependent variable. The spatial autoregressive parameter on the dependent variable (ρ) and several of the average lagged impacts of the independent variables are statistically significant in the Durbin model. This implies that the spatially lagged parameters on the dependent and independent variables significantly improve the model fit. The Durbin model removes spatial dependencies which create inefficient estimates of marginal effects. Indirect impacts of the model are the average of impacts of the characteristics of nearest neighbors. Total impacts and fit statistics of the Durbin models under alternative definitions of neighboring observations are summarized in Table 2. Total impact estimates yield that a residential property experiencing a wildfire within 1.75 miles of a residential property in the five years prior to it's sales date sold for 1 to 1.75 percent less, on average. This impact, however, is insignificant in most specifications that were tested and insignificant in all specifications reported here. Estimates also indicate that direct impacts of living in a neighborhood with greater housing density are negative, while higher housing density of one's neighbors has a positive impact on emerging transactions prices. The total impact of housing density is negative and statistically significant. There appears to be an added premium placed on properties in the wildland-urban 'interface' relative to properties in the wildland-urban 'intermix', but these impacts are insignificant in most specifications. The model yields several interesting results regarding the comparison between desirable and undesirable amenities. For example, every 10 additional houses per square kilometer in a property's census tract will cancel out the percentage increase in sales price from an additional square foot. Depending on the preferred definition of nearest neighbors, it can also be calculated that approximately every 9 recent wildfires within 1.75 miles cancels out the percentage increase from living in the wildland-urban interface. Table 2 summarizes the model results.

Table 2 – Model Results

N =5000 Dependent variable: ln(SalesPrice)	Total impacts = Direct impacts + Indirect impacts of 5 nearest-neighbors' characteristics	Total impacts = Direct impacts + Indirect impacts of 10 nearest-neighbors' characteristics	Total impacts = Direct impacts + Indirect impacts of 15 nearest-neighbors' characteristics	Total impacts = Direct impacts + Indirect impacts of 20 nearest-neighbors' characteristics
(intercept)	-15.279 (8.9750)	-18.06 (11.6720)	-27.37 (14.0760)	21.11 (16.01)
Age of the home	0.00049 + 0.0017* (0.0003) (0.0004)	-0.0004 + 0.0018* (0.0003) (0.0004)	0.0003 + 0.0019* (0.0003) (0.0004)	0.0003 + 0.0018* (0.0003) (0.0005)
Total Finished Square Footage	0.00024* – 0.0001* (<0.00001) (<0.0001)	0.0003* – 0.0002* (<0.0001) (<0.0001)	0.0003* – 0.0002 (<0.0001) (<0.0001)	0.0003* – 0.0002 (<0.0001) (<0.0001)
Number of Bedrooms	0.0510* – 0.0577* (0.0057) (0.0097)	0.0600* – 0.0831* (0.0056) (0.0118)	0.0602* – 0.0920* (0.0057) (0.0133)	0.0613* – 0.0934 (0.0057) (0.0144)
Number of Bathrooms	0.0851* – 0.0152 (0.0067) (0.0117)	0.0808* – 0.0145 (0.0066) (0.0142)	0.0818* – 0.0153 (0.0066) (0.0170)	0.0838* – 0.0141 (0.0067) (0.0177)
Wildfire Count	0.0003 – 0.0177 (0.0078) (0.0088)	-0.0031 – 0.0144 (0.0076) (0.0091)	0.0047 – 0.0147 (0.0075) (0.0090)	0.0052 - 0.0141 (0.0074) (0.0090)
Housing Density of the neighborhood	-0.00007* + 0.00005* (<0.0000) (<0.0000)	-0.00009* + 0.00008* (<0.0001) (<0.0001)	-0.00009* + 0.00008* (<0.0001) (<0.0001)	-0.00009* + 0.00008 (<0.0001) (<0.0001)
Interface Dummy	0.0277 + 0.1327* (0.0403) (0.0414)	0.0598 + 0.0578 (0.0369) (0.0385)	0.0416 + 0.0619 (0.0075) (0.0435)	0.0189 + 0.0750* (0.0337) (0.0362)
Intermix Dummy	0.0391 + 0.0768 (0.0392) (0.0439)	0.0573 + 0.0004 (0.0366) (0.0429)	0.0311 + 0.0011 (0.0356) (0.0435)	0.0073 + 0.0070 (0.0350) (0.0460)
Year of Transaction	0.0199* – 0.0143 (0.0019) (0.0042)	0.0200* – 0.0090 (0.0019) (0.0056)	0.0200* – 0.0052 (0.0020) (0.0068)	0.0203* – 0.0088 (0.00219) (0.0078)
ρ: Log-Liklihood:	0.6446* -878.1291	0.7324* -777.5930	0.7707* -770.2087	0.7934* -791.8037

Note: Standard Errors for estimated parameters are given in parenthesis and "*" indicates significance at the 0.05 level

Discussion

This method for capturing landowner perceptions of fire risk counted nearby wildfire activity within 1.75 miles of each residential property sold within the sample to estimate the negative total impact of recent fire activity on percentage changes in sales prices. The negative total impacts of this wildfire risk factor indicates that homeowners experience a loss from both their own proximity to recent fires and their neighbor's exposure to recent fires. However these impacts are insignificant, which indicate that homeowners may not take this risk factor into account when purchasing residential properties. This could be due to the long-run nature of the chosen risk factor which yields a much smaller percentage decrease in subsequent sales prices than what is found in prior research. Incorporating only more recent wildfires may change the significance of the parameters of wildfire count. It may also be more insightful to isolate the impact of wildfire risk factor's only on homes in the WUI, rather than on homes in both WUI and non-WUI areas. The model considers the value of open space amenities through both the housing density of the neighborhood and the level of vegetation density in a neighborhood and found that interface properties are worth more on average than intermix properties (medium density of vegetation). These results are consistent with prior case studies which find that recent wildfires have a negative impact on land prices and that homeowners prefer medium levels of vegetation density over higher levels of vegetation density in their neighborhood.

Acknowledgements

The authors would like to thank Dr. Jordan Suter for providing helpful comments and feedback. Any mistakes herein are those of the corresponding author.

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