Wildfire Risk and Housing Prices: A Case Study from Colorado Springs

Geoffrey H. Donovan, Patricia A. Champ, and David T. Butry

ABSTRACT. *In 2000, concerned about the risks of wildfires to local homes, the Colorado Springs Fire Department rated the wildfire risk of 35,000 housing parcels within the wildland-urban interface and made its findings available online. We examine the effectiveness of this rating project by comparing the relationship between home price and wildfire risk before and after the information was posted on the Web site. Before the information was available, home price and wildfire risk were positively correlated, whereas, afterwards, they were not.* (JEL R26, Q51)

I. INTRODUCTION

The recent series of severe wildfire seasons in the western United States have increased public awareness of the dangers of wildfire. In particular, concern has focused on the wildland-urban interface, where homes abut forested lands, and fuel loads are often elevated from decades of aggressive wildfire suppression (Arno and Brown 1991). Reducing loss of homes to wildfire was the principal focus of the 2003 Healthy Forests Restoration Act, which has led to additional funding for fuels management activities primarily in the wildland-urban interface. Although reducing wildfire risk has become a priority for federal, state, and local land management agencies, it is not clear that homeowners in the wildland-urban interface understand the risk that wildfire poses to their homes, or what measures can be taken to mitigate this risk. In this study a unique data set allows us to address three related issues: (1) Do parcel-level wildfire risk ratings affect housing prices in a wildland-urban interface area? (2) If there is an effect, is it similar to the effect of a wildfire event on housing prices? and (3) Are there tradeoffs between wildfire risk factors and natural amenity values?

The hazards literature has assessed similar questions for other types of natural disasters such as earthquakes, floods, and hurricanes. However, despite the importance of wildfire as a public policy issue, there have been no studies in the hazards literature that have examined the impact of wildfire risk on the housing market. One reason for this gap in the literature may be the difficulty in estimating wildfire risk. In contrast, the risks of other natural hazards, such as hurricanes and earthquakes, have been well characterized. Indeed, many of these measures of risk have entered the vernacular, for example, "100-year-flood plain" or "earthquake-risk zone." For events such as hurricanes, earthquakes, and floods, scientists can draw on historical data to estimate risk. Historical wildfire occurrence data, however, are of limited use in estimating current wildfire risk for two reasons. First, in many areas the environment has been significantly altered—by clearing forests for housing, for example—such that previous fire history is often a poor indicator of current wildfire risk. Second, a century of aggressive wildfire suppression has significantly reduced the amount of land burned by wildfire. Indeed, in some parts of the wildland-urban interface there has never been a significant

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The authors are, respectively, research forester, USDA Forest Service, PNW Research Station, Portland; economist, USDA Forest Service, Rocky Mountain Research Station, Fort Collins; economist, USDA Forest Service, Southern Research Station, Research Triangle Park. The authors would like to acknowledge the Colorado Springs Fire Department, specifically Cathy Prudhomme, William Mills, Christina Randall, and David Blankinship, for their generous support of this project.

wildfire since the area was developed. Anecdotal evidence suggests that fire exclusion, an absence of reliable risk estimates, and homeowner insurance premiums that are independent of wildfire risk[1] have contributed to many homeowners underestimating the risk that wildfire poses to their homes. Furthermore, wildfire risk rating information is often provided at a very broad scale making it difficult to understand how an individual homeowner can impact risk or how risk differs among homes.

As previously mentioned, the hedonic literature is thin in the area of wildfire risk. To our knowledge, there have been no studies that have directly estimated the impact of wildfire risk on housing prices. Loomis (2004) examined the effect of a large wildfire on housing prices in a community that was two miles from the fire. By looking at housing prices three years before the wildfire and five years after the wildfire, Loomis found a significant drop in post-fire housing prices in the community that was proximate to the wildfire. This result is consistent with studies of the effects of other natural disasters on housing price. For example, Bin and Polasky (2004) observed a larger housing price discount for locating in a flood plain after Hurricane Floyd. Chivers and Flores (2002) also used a hedonic price function to look at discounts associated with purchasing a home in a flood plain and found evidence of a discount only in years immediately after a flood event. Over time, the observed discount diminished. In contrast to these studies, Beron, et al. (1997) noted a small rise in average housing prices (from \$311,000 to \$314,000) in the San Francisco Bay area in the eight months following the 1989 Loma Prieta earthquake. The authors hypothesize that prior to the earthquake, individuals overestimated the potential damage from such an event.

[1] Although some of the major insurance companies are considering denying coverage to homeowners who do not mitigate the wildfire risk on their property, it is not yet an industry wide effort.

II. STUDY AREA AND DATA

Colorado Springs is a city of 361,000 on the front range of the Rocky Mountains in Colorado, approximately 70 miles south of Denver. The study area covers 45 square miles on the western edge of the city bordered by the Pike National Forest, the Air Force Academy, and the Fort Carson Army Base (Figure 1). The elevation in this area varies between 6,000 and 6,800 feet, and the mean annual precipitation is 15 inches. The neighboring forest is predominantly ponderosa pine (*Pinus ponderosa*) and gambel oak (*Quercus gambelii*) with some Douglas fir (*Pseudotsuga menziesii* var. *glauca*) particularly at higher elevations. The area has a mixed-severity fire regime: fires can vary from ground fires that cause little or no overstory mortality to stand-replacing fires. In an average year, the 240,000-acre Pikes Peak Ranger District of the Pike National Forest, which borders the study area, experiences between 40 and 50 wildfire ignitions. However, very few of these ignitions exceed five acres[2] because they are either suppressed by fire crews or because the rain that typically accompanies lightning in this area puts them out naturally. Since European settlement, the study area has experienced two major fires. In 1854, a fire started approximately seven miles southwest of downtown Colorado Springs on Cheyenne Mountain and burned north through the study area before turning west toward the town of South Park. Although exact records are not available, the wildfire certainly burned several hundred thousand acres. In 1950, a wildfire started while land was being cleared for a golf course. In the subsequent fire, nine fire fighters died, and 92 buildings were destroyed with a value of three million dollars (nominal). Since 1950 the area has not had any wildfires. In addition, the Pike National Forest has not conducted any

[2] Personal communication with Christina Randall, Colorado Springs Fire Department, on December 14, 2004.

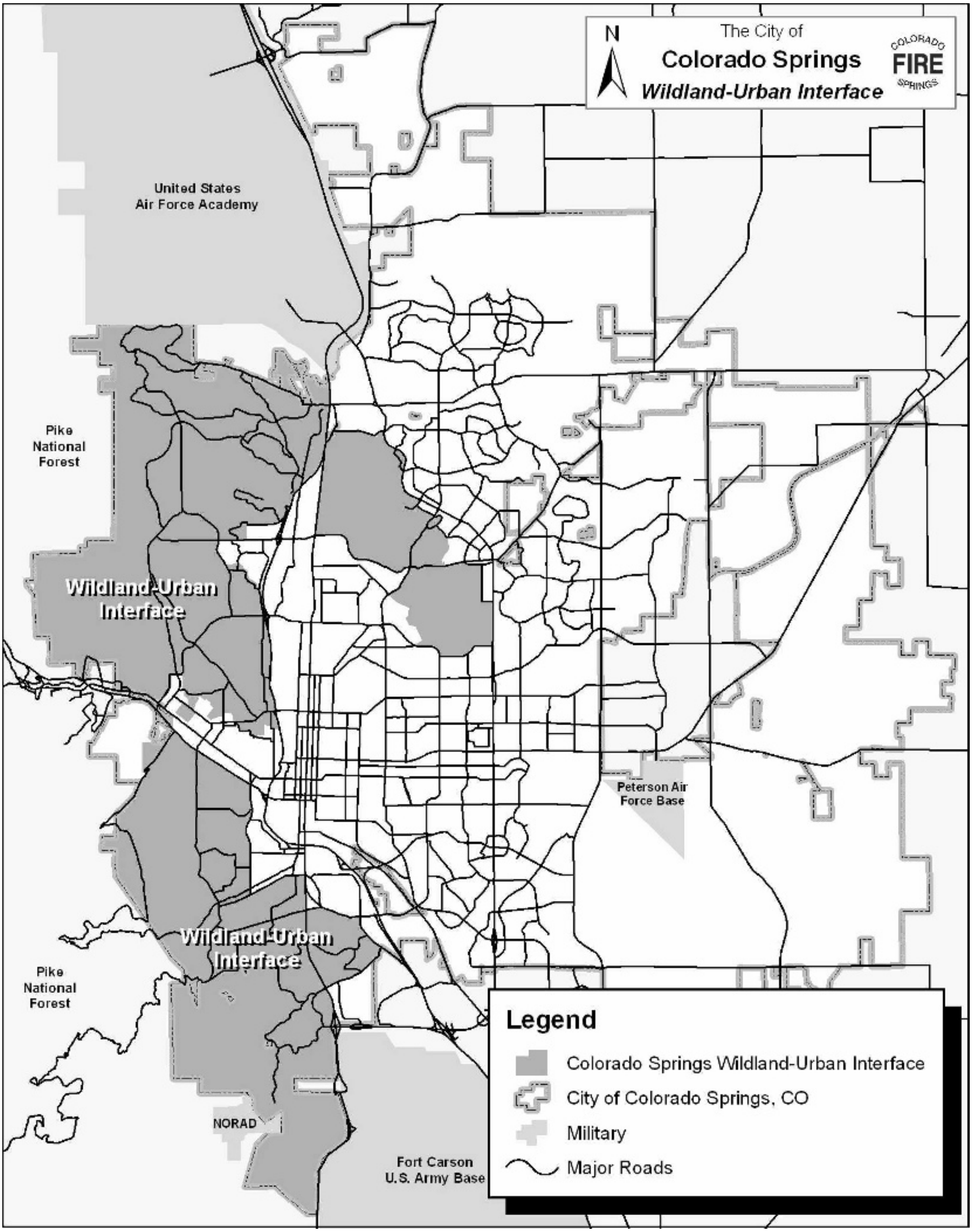

FIGURE 1
Colorado Springs Wildland-Urban Interface

prescribed fire or mechanical fuel treatments in the area.

In 2000, concerned about the risk that wildfire posed to houses in the area, the Colorado Springs Fire Department began a unique project to rate the wildfire risk of 35,000 parcels in the wildland-urban interface and make the information available on a Web site. They believed that existing wildfire risk education efforts, which provided more general information, were ineffective, and that parcel-level wildfire risk assessments would provide the specific information needed to change homeowners' behavior. This view is summarized in the following excerpt from the 2001 Colorado Springs Fire Department Wildfire Mitigation Plan (Colorado Springs Fire Department 2001):

> In general, the public does not perceive a risk from fire in the wildland-urban interface. Further, property owners believe that insurance companies or disaster assistance will always be there to cover losses. When people believe the government will protect them from natural hazards, the damage potential of a catastrophic event increases. Fire prevention efforts, official pronouncements, and media depictions of imminent risk have been shown to have little effect on those in danger. The effects of public education efforts have not been significant when compared to the need. Unless a catastrophic event occurs, wildland/urban interface protection issues generate little interest. (p. 6)

For each parcel, up to 25 variables were used to calculate an overall wildfire risk rating (low, medium, high, very high, or extreme).[3] The fire department is reluctant to publish the specific algorithm it uses to calculate overall wildfire risk ratings, as it believes that ensuing arguments about the relative weights of variables would distract from the goal of increasing awareness of wildfire risk and of encouraging homeowners to mitigate this risk. Although up to 25 variables are used, four variables largely determine a parcel's wildfire risk rating. These are, in order of importance, construction material (roof and siding), proximity to dangerous topography, vegetation density around the house, and the average slope of the surrounding area. In January 2002, employees of the Colorado Springs Fire Department started their outreach program on a very small scale by speaking on request to homeowner groups about wildfire risk—they were not yet fully promoting their wildfire education program. This began on July 1, 2002, when the fire department posted the parcel-level wildfire risk ratings on the Web (http://csfd.springsgov.com/). Homeowners can look up the wildfire risk rating of their house, or any other house, and receive information on how to mitigate wildfire risk. If homeowners take action to reduce the wildfire risk on their property, the fire department will reassess their wildfire risk rating. Since July 2002, the fire department has conducted several thousand reassessments. The most common, and most effective, mitigation measure is to replace a wood shingle roof with a less flammable roofing material. On January 1, 2003, a city ordinance came into force prohibiting the use of wood roofing shingles. Homeowners were not required to replace existing wood shingle roofs, but wood shingles could no longer be used for replacement roofs or for new construction.

Since July 2002, the average number of hits to the Colorado Springs wildfire risk rating Web site has increased every year from approximately 676 per day in 2002 to 870 per day in 2005 (through October). As of June 2005, no insurance companies have used the wildfire risk ratings to determine homeowners' insurance premiums in the study area. The fire department conducted a comprehensive reassessment of the wildfire risk of all houses in the study area beginning in 2005.

The data collected by the Colorado Springs Fire Department allowed us to examine the effect on housing price of both overall wildfire risk ratings and the underlying variables that are used to calculate these ratings. The opportunity to analyze these underlying variables is invaluable, as

[3] The fire department does not specify how much risk reduction results from changing a home's risk rating from high to medium, for example. However, they do estimate that a house with a low risk rating has a 50% chance of surviving a wildfire.

risk from natural disasters can be correlated with natural amenities (Loomis 2004). For example, homes that are located on a ridge are at greater risk of loss due to a wildfire, but they also offer better views. The confounding effects of amenities and wildfire risk on housing price can be untangled by analyzing the underlying variables that make up the overall wildfire risk rating. This is important from a policy perspective, as homeowners are more likely to take mitigation measures that do not reduce the amenity value of their homes.

Data on house sales and housing and neighborhood characteristics were obtained from El Paso County. In the study area, 9,903 houses sold between January 1, 1998, and September 21, 2004. Of these, 6,787 sold pre-Web site, and 3,116 sold post-Web site. A typical house is 27 years old, has 7.8 rooms, 3.5 bedrooms, 2.9 bathrooms, is 1,970 square feet, and has a 16,000-square-foot lot. The mean sale price pre-Web site was $244,000, and $290,000 post-Web site. The lowest sale price was $25,000 (because of concern about sales that were not arms length, we dropped observations with sale prices lower than $25,000) and the highest was $2,500,000.

III. METHODS

The hedonic price method was originally developed by Rosen (1974) and since has been used to estimate the effect of a wide variety of environmental amenities on residential property prices. Typically, house price is regressed on a series of variables that describe the physical characteristics of the house (e.g., area of the house), the neighborhood (e.g., school district), and the environmental amenity under study. Household utility may, therefore, be expressed as

$$U = U(\mathbf{X}, \mathbf{Y}, a)\,, \qquad [1]$$

where $\mathbf{X}$ is a vector of house characteristic variables, $\mathbf{Y}$ is a vector of variables describing characteristics of the neighborhood, and a denotes the environmental amenity under study. We modify this model of household utility by first dividing $\mathbf{X}$ and $\mathbf{Y}$ into variables that affect a house's wildfire risk ($\mathbf{X}^{\mathrm{w}}$and $\mathbf{Y}^{\mathrm{w}}$) and those that don't ($\mathbf{X}^{\mathrm{n}}$ and $\mathbf{Y}^{\mathrm{n}}$). An example of a house characteristic that affects wildfire risk is roofing material, whereas the number of rooms is an example of a characteristic that does not directly affect wildfire risk. Similarly, an example of a neighborhood characteristic that affects wildfire risk is vegetation density, whereas school district does not directly affect wildfire risk.[4] Household utility may, therefore, be expressed as

$$U = U(\mathbf{X}^n, \mathbf{Y}^n, \mathbf{X}^w, \mathbf{Y}^w, R[\mathbf{X}^w, \mathbf{Y}^w])\,, \qquad [2]$$

where R denotes wildfire risk. Note that $\mathbf{X}^w$ and $\mathbf{Y}^w$ enter the above expression both directly and indirectly. This is because some variables that affect wildfire risk, vegetation density for example, may also have amenity value—people often enjoy having trees and other flammable vegetation close to their house.

As will become clear in the following section, we define $\mathbf{X}^w$ and $\mathbf{Y}^w$ so that increases in these variables increase wildfire risk. More formally:

$$\frac{\partial R}{\partial X_i^w} \geq 0, \frac{\partial R}{\partial Y_j^w} \geq 0,$$

where X_i^w and Y_j^w denote representative variables from the $\mathbf{X}^w$ and $\mathbf{Y}^w$ vectors, respectively. In addition, we assume that increases in wildfire risk decrease household utility:

$$\frac{\partial U}{\partial R} \leq 0.$$

Table 1 provides definitions of the independent variables we used for model estimation. Many of the variables are categorical, which we re-coded into dummy variables. Consistent with standard practice, one of the categories is omitted for

[4] In this study we consider "neighborhood" to include anything beyond the structure, both within and beyond the property line.

TABLE 1
DEFINITION OF INDEPENDENT REGRESSION VARIABLES

Variable	Description
CONDO	Dummy variable for construction style (1 if condo, 0 otherwise)
DUPLEX	Dummy variable for construction style (1 if duplex, 0 otherwise)
FRAME	Dummy variable for construction type (1 if frame, 0 otherwise)
TRACT	Dummy variable for construction quality (1 if tract or low, 0 otherwise)
MANSION	Dummy variable for construction quality (1 if mansion, 0 otherwise)
AGE	Year house was built subtracted from 2005
ROOMS	Number of rooms
BASEMENT	Finished basement square footage
ln(HOUSE)	Natural log of total above ground square footage
GARAGE	Garage square footage
H2	Dummy variable for school district (1 if Harrison 2, 0 otherwise)
CS11	Dummy variable for school district (1 if Colorado Springs 11, 0 otherwise)
A20	Dummy variable for school district (1 if Academy 20, 0 otherwise)
ln(LOT)	Natural log of lot square footage
BUSY_MEDIUM	Dummy variable for traffic volume (1 if medium, 0 otherwise)
BUSY_HIGH	Dummy variable for traffic volume (1 if high, 0 otherwise)
SALE_99	Dummy variable for sale year (1 if 1999, 0 otherwise)
SALE_00	Dummy variable for sale year (1 if 2000, 0 otherwise)
SALE_01	Dummy variable for sale year (1 if 2001, 0 otherwise)
SALE_02	Dummy variable for sale year (1 if 2002, 0 otherwise)
SALE_03	Dummy variable for sale year (1 if 2003, 0 otherwise)
SALE_04	Dummy variable for sale year (1 if 2004, 0 otherwise)
EXTREME	Dummy variable for fire risk rating (1 if extreme, 0 otherwise)
VERY_HIGH	Dummy variable fire risk rating (1 if very high, 0 otherwise)
HIGH	Dummy variable for fire risk rating (1 if high, 0 otherwise)
MODERATE	Dummy variable for fire risk rating (1 if moderate, 0 otherwise)
TOP_HIGH	Dummy variable for distance to dangerous topography (1 if <30 feet, 0 otherwise)
TOP_MEDIUM	Dummy variable for distance to dangerous topography (1 if 30–100 feet, 0 otherwise)
ROOF	Dummy variable for roofing material (1 if wood, 0 otherwise)
SIDING	Dummy variable for siding material (1 if wood, 0 otherwise)
VEG_HIGH	Dummy variable for veg. density within 30 feet of house (1 if dense, 0 otherwise)
VEG_MED	Dummy variable for veg. density within 30 feet of house (1 if moderately dense, 0 otherwise)
SLOPE	Average slope (%) within 150 feet of house

each of the variables. The construction style variable was re-coded into three dummy variables, CONDO, DUPLEX, and the omitted variable that is a composite variable of all detached single-family home construction styles. Construction type is FRAME or masonry, which is omitted. There are three categories for construction quality, TRACT, MANSION, and custom, which is omitted. There are four school districts in the study area, Harrison 2 (H2), Colorado Springs 11 (CS11), Academy 20 (A20), and the omitted district, Manitou Springs School District 14. Pre-Web site, the omitted sale year is 1998, and post-Web site, the omitted sale year is 2002. There are five overall wildfire risk rating categories: EXTREME, VERY_HIGH, HIGH, MODERATE, and low which is omitted. The topography variables measure the distance from the parcel to dangerous topography.[5] TOP_HIGH is the dummy variable if the parcel is located less than 30 feet from dangerous topography. TOP_MEDIUM is the dummy variable if the parcel is located 30 to 100 feet from dangerous topography. The omitted variable is for the category designating that the parcel is located greater than 100 feet from dangerous topography. The vegetation density variable was also re-coded into dummy variables. VEG_HIGH is the dummy variable for dense vegetation within 30 feet of the house. VEG_MEDIUM is the dummy variable for moderately dense

[5] Dangerous topography includes V-shaped canyons, ridges, and saddles.

vegetation within 30 feet of the house. The omitted vegetation density variable is low vegetation density within 30 feet of house.

There is little theoretical guidance on the choice of functional form for the hedonic price function (Taylor 2003). We pragmatically use a log functional form; the natural log of house price is related to the natural log of house size and lot size with all other variables entering linearly. We also experimented with other functional forms (linear, quadratic, etc.) and found that our results were largely insensitive to functional form.

Spatial Dependence and Regression Analysis

Recent hedonic studies recognize the importance of spatial relationships and are beginning to explicitly account for them (Kim, Phips, and Anselin 2003). Attention has focused on two types of spatial processes—spatial lag and spatial error dependence (Anselin and Bera 1998). Spatial lag dependence, or spatial autocorrelation, occurs when the dependent variable is spatially autocorrelated, meaning an observation's value is partly a function of its spatial neighbors' values (positive autocorrelation). For instance in the hedonic setting, spatial lag dependence implies that home *i*'s selling price is a function of home *j*'s selling price (or all homes in the relevant spatial neighborhood). In a regression context, spatial lag dependence can be represented as

$$\mathbf{P} = \rho \mathbf{W}_1 \mathbf{P} + \mathbf{ZB} + \mu \,, \qquad [3]$$

where $\mathbf{P}$ is an $N \times 1$ vector denoting sale price, $\mathbf{Z}$ is an $N \times K$ matrix of property characteristics, $\mathbf{B}$ is a $K \times 1$ vector of coefficients, ρ is the (scalar) spatial lag coefficient, $\mathbf{W_1}$ is an $N \times N$ spatial weighting matrix describing the spatial lag process, and μ is an $N \times 1$ vector of the i.i.d error term.

The second process is spatial error dependence, which occurs when regression residuals are spatially correlated. Spatial error dependence may occur if measurement error is spatially autocorrelated (Anselin and Bera 1998). In a regression context, spatial error dependence may be represented as

$$\mathbf{P} = \mathbf{ZB} + \varepsilon, \text{ where } \varepsilon = \lambda \mathbf{W_2} \varepsilon + \mu \,, \qquad [4]$$

where again, $\mathbf{P}$ is an $N \times 1$ vector denoting sale price, $\mathbf{Z}$ is an $N \times K$ matrix of property characteristics, $\mathbf{B}$ is a $K \times 1$ vector of coefficients, λ is the (scalar) spatial error coefficient, $\mathbf{W_2}$ is an $N \times N$ spatial weighting matrix describing the spatial error process, ε is an $N \times 1$ vector of the spatial error, and μ is an $N \times 1$ vector of the i.i.d error term.

A combined spatial lag and error model takes the following form (assuming $\mathbf{W_1} = \mathbf{W_2} = \mathbf{W}$):

$$\mathbf{P} = (\rho + \lambda)\mathbf{WP} - \rho\lambda \mathbf{W}^2\mathbf{P} + \mathbf{ZB} - \lambda \mathbf{WZB} + \mu \,. \qquad [5]$$

If no spatial dependence exists, implying ρ and λ equal zero, then equations [3] through [5] reduce to a linear in parameters regression model. From a statistical standpoint, spatial lag dependence is a more serious problem than spatial error dependence, as failing to account for spatial lag dependence will lead to biased and inconsistent parameter estimates, whereas failing to account for spatial error dependence leads to inefficiency (Anselin and Bera 1998).

Maximum likelihood estimation is used to estimate equations [3] through [5], with the parameters ρ and λ estimated during the regression step. The spatial weight matrix, $\mathbf{W}$, however, must be specified before estimation. The weight matrix is an $N \times N$ matrix describing the spatial process between observations. For instance, matrix element w_{ij} quantifies the influence neighbor j has on observation i. The literature provides little guidance on how to determine the appropriate form for the weight matrix, but several different specifications exist (Anselin 1988). A review of the subset of the hedonic literature that pertains to spatial processes suggests that spatial weights matrices are often specified arbi-

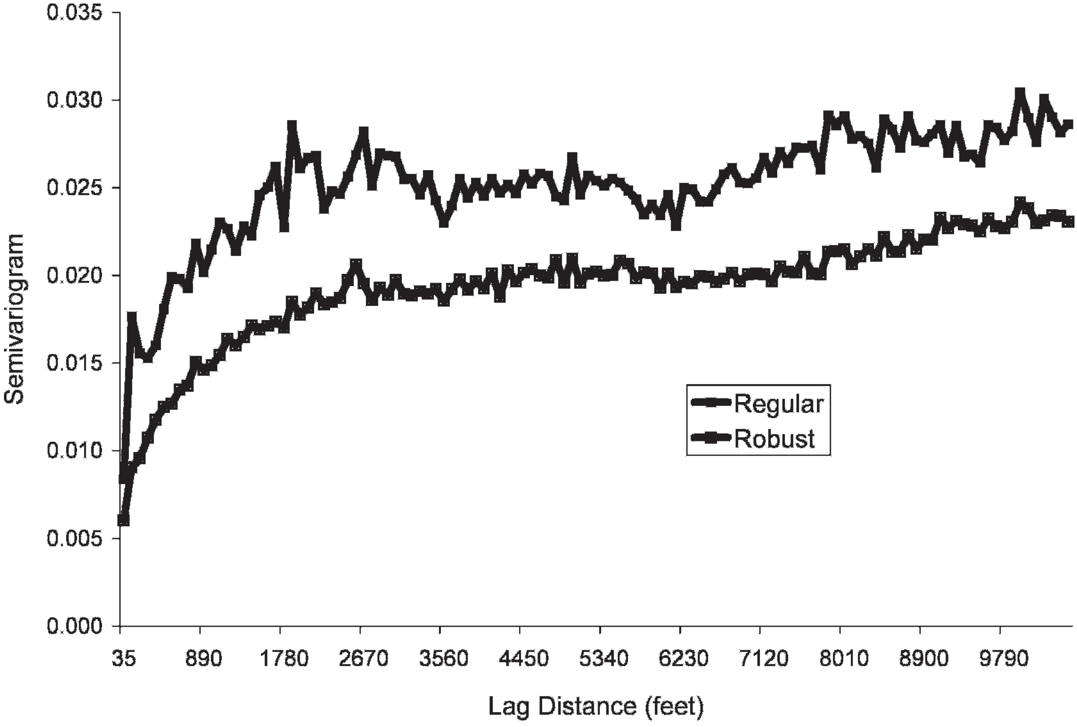

FIGURE 2
SEMI-VARIOGRAM OF RESIDUALS FROM NON-SPATIAL REGRESSION OF WILDFIRE RISK RATINGS AND HOUSE AND NEIGHBORHOOD CHARACTERISTICS ON HOUSE PRICE POST-WEB SITE

trarily, which raises the possibility of introducing an additional source of error. To avoid an arbitrary specification, we use a semi-variogram of the ordinary least squares (OLS) non-spatial model residuals to determine whether spatial dependence exists, and if so, its extent (Figure 2).[6] The semi-variogram suggests that spatial dependence is present, is non-linear, and curtails after approximately half a mile. Unfortunately based on a semi-variogram of the residuals, we cannot determine whether the presence of spatial dependence is due to a spatial lag or a spatial error process. To account for the nonlinearity, we specify the elements of **W** (we assume $\mathbf{W_1} = \mathbf{W_2}$)[7] to be one over the square of distance, and curtail this relationship at half a mile. This spatial weighting implies that neighbors located closer in space have more influence on one another than more distant neighbors, and those neighbors beyond a half a mile away, have no influence. Anecdotally, real estate agents in the area that we contacted generally supported this characterization. For computational efficiency we row-standardize **W**. Also, standardizing the weight matrix ensures the parameter coefficients ρ and λ will be bounded by –1 and 1 (Anselin and Bera 1998).

[6] The difference between a regular and a robust semi-variogram is the latter is less sensitive to influential outliers. See Cressie (1993) for a detailed discussion of semi-variograms.

[7] Identification of the spatial lag and spatial error terms (in a joint model) requires that either $\mathbf{W_1} \neq W_2$ or the existence of one or more explanatory variables in the model (Anselin and Bera). The latter condition holds in our models.

Model Estimation

In the following section we present four models. The first two models estimate the effect of the overall wildfire risk ratings on housing price both pre- and post-Web site. The second two models estimate the effect on housing price of the underlying variables used to calculate a parcel's wildfire risk rating both pre- and post-Web site. For convenience, we refer to the first two models as "risk" models and the second two models as "amenity" models as some of the underlying variables have positive amenity values.[8]

The likelihood function used for the spatial model is as follows (Case 1991):

$$L_i = \ln(1 - \rho\omega_i) + \ln(1 - \lambda\omega_i) - 0.5(2\pi) - 0.5(\sigma^2) - 0.5(p_i - (\rho + \lambda)(\mathbf{W}p)_i + (\rho\lambda)(\mathbf{W}^2p)_i - \mathbf{Z}_i\mathbf{B} + \lambda(\mathbf{WZ}_i)\mathbf{B})^2 / \sigma^2, \quad [6]$$

where ω_i denotes the eigenvalues of the weight matrix, $\mathbf{Z_i}$ is a $1 \times K$ vector of all explanatory variables for the *i*th observation, $\mathbf{WZ_i}$ is a $1 \times K$ vector (all the explanatory variables, for the *i*th observation are weighted by the $\mathbf{W}$ matrix), and assuming normally distributed disturbances. Since the row-standardized weight matrix is asymmetric, real eigenvalues are not guaranteed; however, equivalent real eigenvalues can be constructed based on the symmetric, non-row-standardized weight matrix (Ord 1975).[9] The null hypothesis of no spatial dependence (that $\rho = 0$, $\lambda = 0$, and jointly that $\rho = \lambda = 0$), is examined by using a likelihood ratio test.

IV. RESULTS

Spatial Dependence

We find that the joint spatial lag and error specification achieves the largest log-likelihood relative to the OLS, spatial lag only, and spatial error only specifications (Table 2). The spatial components, ρ and λ, are both individually and jointly significant, based on the likelihood ratio tests, implying the non-spatial OLS parameter estimates are biased and inconsistent and that the models are inefficient. The likelihood ratio tests, testing the significances of the spatial parameters, are performed using the spatial lag and error combined model as the unrestricted model and the spatial lag (error) model as the restricted model to test the significance of the spatial error (lag) term (see Anselin and Bera 1998 for details).[10] A joint test of spatial lag and spatial error dependence is performed using, again, the combined model as the unrestricted model and the OLS model as the restricted model. We found statistical evidence of both spatial lag and spatial error dependence. Therefore we proceed to estimate all models with the joint spatial lag and error specifications.

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[8] We pragmatically chose to estimate pre- and post-Web site models, rather that a combined model using a dummy variable to denote pre- or post-Web site sales, because the combined data set was too large to estimate a spatially explicit model (using a processor with 2GB of RAM). Unfortunately, our inability to estimate a combined model limited our ability to test for a structural change in the data. We did, however, find no statistically significant difference in independent variable means between pre- and post-Web site samples, which at least suggests that the observed differences are not due to sampling bias.

[9] The eigenvalues are required since in maximum likelihood estimation, where some parameters appear as nonlinear functions of the dependent variable, we need to include the natural log of the Jacobian of transformation (see Greene 2000). In the case of the spatial model we need the determinant of the Jacobian of transformation, which equals $|\mathbf{I} - \rho\mathbf{W}|$, for the spatial lag model, and $|\mathbf{I} - \lambda\mathbf{W}|$, for the spatial error model (in the combined model, both terms are included) (for greater discussion see Anselin and Bera 1998; Anselin and Hudak 1992). Ord (1975) shows that $|\mathbf{I} - \rho\mathbf{W}| = \prod_{i=1}^{n}(1 - \rho\omega_i)$, where ω_i are the *i*th eigenvalues of $\mathbf{W}$. Since the weight matrix is row standardized to one, which is commonly done to ensure the spatial parameters are bounded by −1 and +1 (becoming a spatial correlation coefficient), this makes the weight matrix asymmetric. Eigenvalues of an asymmetric matrix make be real or imaginary, however the eigenvalues of a symmetric matrix are guaranteed to be real (Greene 2000). Ord (1975) shows that while $\mathbf{W}$ and $\mathbf{W}^S$ (where $\mathbf{W}^S = \mathbf{D}^{.5}\mathbf{WD}^{.5}$) have the same eigenvalues, $\mathbf{W}^S$ is symmetric and thus is guaranteed to have real eigenvalues, where D is the diagonal matrix of $\mathbf{W}^A\mathbf{I}$, $\mathbf{W}^A$ is the non-row standardized weight matrix, and $\mathbf{I}$ is the identity matrix.

[10] A few alternative methods exist for testing the spatial parameters besides the two-directional likelihood ratio test described above (see Anselin and Bera 1998 and Anselin et al. 1996 for details).

TABLE 2

LIKELIHOOD RATIO (LR) TESTS FOR OLS, SPATIAL LAG, SPATIAL ERROR, AND COMBINED MODELS

Model	Log Likelihood	Parameter Tested	Unrestricted Model	Restricted Model	LR*
		Pre-Web Site Risk Model			
OLS	−1887.77	n/a	n/a	n/a	n/a
Spatial Lag	−1571.67	Spatial Error	Spatial Lag & Error	Spatial Lag	9.41
Spatial Error	−1592.38	Spatial Lag	Spatial Lag & Error	Spatial Error	50.83
Spatial Lag and Error	−1566.97	Joint (Lag & Error)	Spatial Lag & Error	OLS	641.60
		Pre-Web Site Amenity Model			
OLS	−1870.74	n/a	n/a	n/a	n/a
Spatial Lag	−1562.92	Spatial Error	Spatial Lag and Error	Spatial Lag	8.11
Spatial Error	−1586.10	Spatial Lag	Spatial Lag and Error	Spatial Error	54.46
Spatial Lag and Error	−1558.87	Joint (Lag and Error)	Spatial Lag and Error	OLS	623.75
		Post-Web Site Risk Rating Model			
OLS	873.35	n/a	n/a	n/a	n/a
Spatial Lag	1070.18	Spatial Error	Spatial Lag and Error	Spatial Lag	91.48
Spatial Error	1104.12	Spatial Lag	Spatial Lag and Error	Spatial Error	23.60
Spatial Lag and Error	1115.92	Joint (Lag and Error)	Spatial Lag and Error	OLS	485.14
		Post-Web Site Amenity Model			
OLS	912.94	n/a	n/a	n/a	n/a
Spatial Lag	1099.82	Spatial Error	Spatial Lag and Error	Spatial Lag	87.11
Spatial Error		*Model Would Not Converge*			
Spatial Lag and Error	1143.38	Joint (Lag and Error)	Spatial Lag and Error	OLS	460.88

Note: *95% critical value of chi-square with 1df = 3.84; 2 df = 5.99.

TABLE 3

REGRESSION RESULTS FOR PRE-WEB SITE RISK MODEL

Variable	Coefficient	Standard Error	*p*-value	Marginal Effect ($)
RHO	0.330	0.232E-01	< 0.0001	
LAMBDA	0.142	0.285E-01	< 0.0001	
CONSTANT	4.73	0.289	< 0.0001	
CONDO	6.43E-02	3.02E-02	0.0337	27,261
DUPLEX	−6.47E-02	3.11E-02	0.0375	−24,911
FRAME	−3.70E-02	2.73E-02	0.176	−15,366
TRACT	−0.115	1.94E-02	< 0.0001	−45,107
MANSION	8.64E-02	1.10E-02	< 0.0001	39,368
AGE	8.79E-04	3.53E-04	0.0127	355
ROOMS	5.16E-03	2.61E-03	0.0486	2,092
BASEMENT	8.29E-05	6.75E-06	< 0.0001	34
ln(HOUSE)	0.390	1.78E-02	< 0.0001	85
GARAGE	4.15E-05	2.22E-05	0.0621	17
H2	−2.74E-03	6.86E-02	0.968	−1,109
CS11	−4.23E-02	1.20E-02	0.0004	−16,558
A20	−2.71E-02	1.45E-02	0.0625	−10,728
ln(LOT)	3.43E-02	6.26E-03	< 0.0001	2
BUSY_MEDIUM	−1.80E-02	8.89E-03	0.0431	−7,174
BUSY_HIGH	1.05E-02	1.43E-02	0.464	4,208
SALE_99	9.18E-02	1.02E-02	< 0.0001	25,467
SALE_00	0.196	1.14E-02	< 0.0001	58,937
SALE_01	0.278	1.19E-02	< 0.0001	89,194
SALE_02	0.298	1.61E-02	< 0.0001	97,153
EXTREME	4.80E-02	1.82E-02	0.0083	20,101
VERY_HIGH	5.90E-02	1.51E-02	0.0001	24,914
HIGH	4.97E-02	1.42E-02	0.0005	20,839
MEDIUM	4.69E-02	1.35E-02	0.0005	19,624
R-squared	0.625			

TABLE 4
REGRESSION RESULTS FOR POST-WEB SITE RISK MODEL

Variable	Coefficient	Standard Error	p-value	Marginal Effect ($)
RHO	0.143	2.00E-02	< 0.0001	
LAMBDA	0.373	2.54E-02	< 0.0001	
CONSTANT	6.95	0.250	< 0.0001	
CONDO	4.22E-02	2.03E-02	0.0376	12,947
DUPLEX	−6.80E-02	2.70E-02	0.0120	−19,566
FRAME	−3.65E-02	1.27E-02	0.0040	−11,160
TRACT	−0.160	1.24E-02	< 0.0001	−43,684
MANSION	2.04E-01	1.31E-02	< 0.0001	68,937
AGE	−1.41E-03	2.45E-04	< 0.0001	−422
ROOMS	−4.53E-05	2.58E-03	0.986	−14
BASEMENT	1.32E-04	5.70E-06	< 0.0001	39
ln(HOUSE)	0.433	1.37E-02	< 0.0001	66
GARAGE	1.33E-04	1.89E-05	< 0.0001	40
H2	−9.19E-02	6.35E-02	0.148	−29,035
CS11	−5.85E-02	1.44E-02	< 0.0001	−18,841
A20	−1.06E-01	1.76E-01	< 0.0001	−33,221
ln(LOT)	4.76E-02	3.70E-03	< 0.0001	1
BUSY_MEDIUM	−1.15E-02	8.92E-03	0.197	−3,419
BUSY_HIGH	1.97E-02	1.06E-02	0.0630	5,964
SALE_03	2.48E-02	8.17E-03	0.0024	7,531
SALE_04	8.37E-02	9.00E-03	< 0.0001	26,316
EXTREME	1.79E-02	1.75E-02	0.308	5,414
VERY_HIGH	2.18E-02	1.52E-02	0.153	6,608
HIGH	1.73E-02	1.36E-02	0.205	5,230
MEDIUM	6.70E-03	1.26E-02	0.594	2,013
R-squared	0.871			

Marginal effects were evaluated with continuous variables set to their sample means, a sale year of 2002, and the dummy variables FRAME and H2 set to 1. In addition, following Kim, Phips, and Anselin. (2003), the marginal effect of a variable was calculated as its reported coefficient times the spatial multiplier, $1/(1-\rho)$. Note the greater the spatial dependence, and hence the larger ρ, the larger the spatial multiplier (Tables 3–6). Thus, the marginal effects of explanatory variables in a spatial hedonic model with a lag process are composed of two components—the direct (non-spatial) influence the variables has on house price plus a spatial enhancement due to interaction with neighboring houses.

Comparing the spatial with the OLS models, we find that accounting for spatial dependence is not only statistically significant, but economically significant as well. We calculated the absolute percent bias in the OLS marginal effects and compared these to the spatial lag and error combined marginal effects for each of the non-spatial variables (not including the constant term). The absolute percentage of bias of the OLS marginal effects average 37% in the pre-Web site rating model, 36% in the pre-Web site amenity model, 167% in the post-Web site rating model, and 76% in the post-Web site amenity model.

Housing and Neighborhood Characteristics

The effects of housing and neighborhood characteristics are consistent with economic theory and are largely consistent across the four models (Tables 3–6). In particular, increases in house, lot, basement, and garage square footage increase house price in all models. We note, however, the following inconsistent or unexpected results. The positive effect on price of the CONDO variable was unexpected. Sales of condominiums make up a relatively small proportion of total sales in the study area. For example, pre-Web site less than 8% of

TABLE 5
Regression Results for Pre-Web Site Amenity Model

Variable	Coefficient	Standard Error	p-value	Marginal Effect ($)
RHO	0.334	2.27E-02	< 0.0001	
LAMBDA	0.130	2.80E-02	< 0.0001	
CONSTANT	4.75	0.282	< 0.0001	
CONDO	6.71E-02	3.01E-02	0.0258	29,466
DUPLEX	−6.06E-02	3.09E-02	0.0501	−24,177
FRAME	−3.27E-02	2.75E-02	0.2340	−13,990
TRACT	−0.111	1.95E-02	< 0.0001	−52,328
MANSION	8.57E-02	1.09E-02	< 0.0001	38,174
AGE	8.64E-04	3.60E-04	0.0165	361
ROOMS	5.12E-03	2.61E-03	0.0502	2,146
BASEMENT	8.48E-05	6.76E-06	< 0.0001	36
ln(HOUSE)	0.386	1.79E-02	< 0.0001	87
GARAGE	4.26E-05	2.22E-05	0.0554	18
H2	−7.26E-03	6.90E-02	0.916	−3,047
CS11	−4.08E-02	1.20E-02	0.0007	−16,699
A20	−2.08E-02	1.46E-02	0.153	−8,641
ln(LOT)	3.55E-02	6.31E-03	< 0.0001	2
BUSY_MEDIUM	−1.42E-02	8.79E-03	0.106	−5,864
BUSY_HIGH	1.08E-02	1.42E-02	0.448	4,545
SALE_99	9.20E-02	1.03E-02	< 0.0001	26,403
SALE_00	1.96E-01	1.15E-02	< 0.0001	60,988
SALE_01	2.78E-01	1.20E-02	< 0.0001	92,332
SALE_02	2.96E-01	1.60E-02	< 0.0001	99,744
TOP_HIGH	3.53E-02	1.27E-02	0.0055	15,132
TOP_MEDIUM	1.29E-02	1.03E-02	0.210	5,437
ROOF	2.77E-02	1.58E-02	0.0791	11,806
SIDING	−1.28E-02	1.44E-02	0.374	−5,291
VEG_HIGH	2.15E-02	1.34E-02	0.108	9,121
VEG_MED	6.64E-03	9.80E-03	0.498	2,786
SLOPE	−5.18E-03	1.03E-03	< 0.0001	−2,153
R-squared	0.626			

all sales were condominiums. It is possible, therefore, that a few condominium developments with particularly desirable characteristics influenced the results. The change in the coefficient on age from positive pre-Web site to negative post-Web site was unexpected. One explanation could be that post-Web site, older homes were less attractive because they were in need of more work to reduce the risk of wildfire.

Overall Wildfire Risk Ratings

A comparison of the results in Tables 3 and 4 show how the availability of parcel-level wildfire risk information affected the relationship between overall risk ratings and housing price. As previously noted, some of the underlying variables used to calculate overall wildfire risk ratings also have amenity value. For example, some home buyers prefer a densely wooded lot or a house on a ridge. The results in Table 3 suggest that pre-Web site, these positive amenity values outweighed the negative effect of wildfire risk on housing price, as the coefficients on the overall risk ratings are positive and significant. However post-Web site (Table 4), the coefficients on the overall risk rating variables were no longer significant. This result suggests that post Web site, the positive amenity effects were offset by the increased wildfire risk associated with such parcels. In addition, we found that the total price of a representative house declined post-Web site. For example, using the same independent variable values used to calculate marginal effects, the price of a representative pre-Web site house was $290,000. Substituting these same values

TABLE 6
Regression Results for Post-Web Site Amenity Model

Variable	Coefficient	Standard Error	p-value	Marginal Effect ($)
RHO	0.141	2.00E-02	< 0.0001	
LAMBDA	0.364	2.57E-02	< 0.0001	
CONSTANT	7.01	0.248	< 0.0001	
CONDO	3.77E-02	1.96E-02	0.0545	11,635
DUPLEX	−6.37E-02	2.64E-02	0.0157	−18,533
FRAME	−3.12E-02	1.26E-02	0.0135	−9,592
TRACT	−0.165	1.22E-02	< 0.0001	−45,318
MANSION	1.89E-01	1.27E-02	< 0.001	63,819
AGE	−1.19E-03	2.40E-02	< 0.0001	−359
ROOMS	1.41E-04	2.59E-03	0.957	43
BASEMENT	1.28E-04	5.85E-06	< 0.0001	39
ln(HOUSE)	0.432	1.37E-02	< 0.0001	67
GARAGE	1.34E-04	1.88E-05	< 0.0001	41
H2	−9.58E-02	6.76E-02	0.156	−30,595
CS11	−6.32E-02	1.41E-02	< 0.0001	−20,564
A20	−1.07E-01	1.77E-02	< 0.0001	−33,954
ln(LOT)	4.57E-02	3.70E-03	< 0.0001	1
BUSY_MEDIUM	−1.20E-02	8.76E-03	0.172	−3,597
BUSY_HIGH	1.05E-02	1.09E-02	0.3380	3,190
SALE_03	2.60E-02	8.10E-03	0.0013	7,969
SALE_04	8.48E-02	9.07E-03	< 0.0001	29,906
TOP_HIGH	7.81E-02	1.22E-02	< 0.0001	24,682
TOP_MEDIUM	2.67E-02	8.60E-03	0.0019	8,187
ROOF	−1.66E-02	9.19E-03	0.0702	−4,963
SIDING	−2.05E-02	9.44E-03	0.0297	−6,115
VEG_HIGH	2.70E-03	1.25E-02	0.829	817
VEG_MED	1.10E-02	9.00E-03	0.221	3,342
SLOPE	−1.17E-03	9.78E-04	0.231	−353
R-squared	0.873			

into the post-Web site amenity model gave a price of $250,000.

A common finding in previous hedonic studies is that the effect of a natural disaster on the housing market diminishes over time. For example, Chivers and Flores (2002) found that a flood had an impact on the housing market only in years immediately after the event. Our post-Web site sales data were limited to two years. Nonetheless, we re-specified the post-Web site risk model using a dummy variable to separate post-Web site sales into two groups: early sales that occurred between July 1, 2002 and July 1, 2003 and late sales that occurred between July 2, 2003 and September 21, 2004 (Table 7). Using a Wald test to jointly test for differences in the

TABLE 7
A Comparison of Coefficients on Risk Variables in the First and Second Years Post-Web Site

Variable	Coefficient	Standard Error	p-value
MODERATE EARLY	−1.61E-02	1.45E-02	0.264
MODERATE LATE	2.36E-02	1.58E-02	0.134
HIGH EARLY	−5.34E-03	1.71E-02	0.755
HIGH LATE	3.45E-02	1.61E-02	0.0320
VERY_HIGH EARLY	−3.07E-03	1.91E-02	0.872
VERY_HIGH LATE	4.28E-02	1.82E-02	0.0189
EXTREME EARLY	−3.23E-02	2.13E-02	0.128
EXTREME LATE	5.74E-02	2.07E-02	0.0055

TABLE 8
A Comparison of Coefficients on House and Siding Variables in the First and Second Years Post-Web Site

Variable	Coefficient	Standard Error	p-value
ROOF EARLY	−3.16E-02	1.38E-02	0.0224
ROOF LATE	−6.83E-03	1.19E-02	0.5672
SIDING EARLY	−2.66E-02	1.44E-02	0.0657
SIDING LATE	−1.54E-02	1.19E-02	0.1949

coefficients on the four risk variables between early and late sales, we found a significant difference ($p = 0.00121$). This suggests that the effect of the Web site appears to be fleeting, although this result should be confirmed by analyzing post-Web site sales over a longer period.

Underlying Risk Variables

We estimated pre- and post-Web site models including the four variables that are weighted most heavily when calculating a parcel's overall risk rating: construction materials, proximity to dangerous topography, vegetation density, and the slope of the landscape within 150 feet of the house (Tables 5 and 6).

Pre-Web site, the effect of dangerous topography 30 feet or less from a house (TOP_HIGH) was positive and significant (Table 5). This result endured post-Web site, and, in addition, the effect of dangerous topography 30–100 feet from a home (TOP_MEDIUM) became positive and significant (Table 6). The effect of steeper slopes within 150 feet of a house was negative and significant pre-Web site but insignificant post-Web site. This result may appear counterintuitive, if the Web site raised homebuyers' awareness of wildfire, we would expect the slope variable to remain significant post-Web site. Conversations with residents suggest that this result may be due to a decrease in availability of flatter building sites. As these sites became more scarce, buyers may have been more willing to accept sites with higher slopes.

Pre-Web site, a wood roof had a significant and positive impact on housing price. However, post-Web site, a wood roof had a significant and *negative* effect on housing price. Similarly, wood siding had no significant effect on housing price pre-Web site, but had a significant and *negative* effect post-Web site. Vegetation density within 30 feet of the home did not significantly impact housing price either pre- or post-Web site.

To see if the effect of the Web site on preferences for flammable building materials diminished over time, we re-specified the post-Web site amenity model distinguishing between early and late sales (Table 8). A Wald test found no joint difference ($p = 0.227$) in the coefficients on ROOF and SIDING between early and late sales. Unlike the risk variables, it appears post-Web site preferences for flammable building materials remains stable over time, although again, the analysis is limited to a two-year period.

The above results can be interpreted in a formal household utility framework by using the nomenclature developed earlier. For a neighborhood characteristic that affects wildfire risk and is positively correlated with house price, such as proximity to dangerous topography, we can say that

$$\frac{\partial U}{\partial Y^w} > \frac{\partial R}{\partial Y^w} * \frac{\partial U}{\partial R}. \qquad [7]$$

The same relationship holds for a house characteristic that affects wildfire risk and is positively correlated with price, such as roofing material. There are two possible explanations for insignificant coefficients on variables that affect wildfire risk. First, a variable may have no amenity value, and have no perceived effect on wildfire risk. Second, a variable's amenity value may be counteracted by its affect on wildfire risk. Formally, using a neighborhood characteristic as an example:

$$\frac{\partial U}{\partial Y^w} \approx \frac{\partial R}{\partial Y^w} * \frac{\partial U}{\partial R}. \qquad [8]$$

Although the manner in which amenity values, wildfire risk, and household utility interact is not clear for all variables, pre-Web site, it is clear on aggregate. That is, for the house and neighborhood characteristics considered, positive amenity values outweigh the negative effects of wildfire risk. Formally:

$$\sum_{n}^{i=1} \frac{\partial U}{\partial X_i^w} + \sum_{m}^{j=1} \frac{\partial U}{\partial Y_j^w} >$$
$$\sum_{n}^{i=1} \frac{\partial R}{\partial X_i^w} * \frac{\partial U}{\partial R} + \sum_{m}^{j=1} \frac{\partial R}{\partial Y_j^w} * \frac{\partial U}{\partial R}. \qquad [9]$$

In contrast, post-Web site, the coefficients on wildfire risk variables are no longer significant (Table 4). The results from the post-Web site amenity model provide an explanation of this loss in significance. The most striking difference between the pre- and post-Web site amenity models is the change in the coefficients on the roof and siding variables. The roof coefficient changes from positive and significant to negative and significant, and the siding coefficient changes from insignificant to negative and significant. Because housing material is the most important determinant of a house's wildfire risk rating, it is not surprising that the overall wildfire risk coefficients lose their significance as a result. In contrast to the housing material coefficients, the topography coefficients remain positive in the post-Web site amenity models and increase in size. This may be because, despite the importance of proximity to dangerous topography to overall wildfire risk, the fire department does not emphasize it in its risk mitigation advice to homeowners. Instead, the fire department emphasizes measures that homeowners can take to mitigate their current homes' wildfire risk, and there is little, if anything, that can be done to change an existing house's proximity to dangerous topography.

V. DISCUSSION

This study estimated the effect of wildfire risk on housing price in Colorado Spring's wildland-urban interface both before and after parcel-level wildfire risk ratings were made available on a Web site. Pre-Web site, overall wildfire risk ratings were positively related to housing price, suggesting that the positive amenity value of the house and neighborhood characteristics that affect a house's wildfire risk outweighed the perceived loss in household utility from increased wildfire risk. However, this relationship between overall wildfire risk rating and housing price was not observed post-Web site, suggesting that the availability of parcel-level wildfire risk ratings contributed to an increased awareness of wildfire risk. We found some evidence that this effect diminished over time. This change in awareness was manifested largely by a change in preferences for wood roofs and siding. A positive correlation between proximity to dangerous topography and house price was observed both pre- and post-Web site. This result may be partly due to a lack of emphasis that the fire department places on proximity to dangerous topography in the advice they give to homeowners. The fire department also emphasizes the risk posed by high vegetation density around a house. Unlike housing material, there is only modest evidence of a change in preferences for vegetation density. However, it is possible that home buyers are concerned about the wildfire risk posed by dense vegetation but do not let that concern affect their housing decision because they think they can thin the vegetation at a relatively low cost after they purchase the home. In comparison, the cost of replacing a wood roof or wood siding is substantial, and the cost of changing the topography around a house is prohibitive.

The availability of house and neighborhood characteristics in combination with parcel-level wildfire risk data provide us with a unique insight into the relationship between amenity values and risk. Results suggest that looking at the effect of wildfire risk on house price without accounting for amenity values may be misleading. For example, the results from the pre-Web site overall wildfire risk rating model (Table 3) provide prima facie evidence of a positive relationship between wildfire risk and house price. It is only after examining the results from the corresponding amenity model that a more complete picture of the relationship between wildfire risk, amenity values, and housing price emerges.

This study differs in another significant way from others that have studied the effect of natural hazards on housing price. These studies fall into two categories: those that evaluate the effect of natural hazard risk on house price and those that examine this effect before and after a natural disaster occurs. In this study we examine whether an educational campaign can have the same effect as a natural disaster. Results do not indicate whether this educational campaign had the same quantitative effect as a wildfire would have, but the qualitative effect observed—a more negative effect of risk on house price, which diminishes over time—is consistent with the literature on other natural disasters. It would be useful to repeat this study in a few years to see if the observed decline in the effect of the educational campaign continues. If this were observed, it would suggest that educational campaigns may need to be continually promoted or periodically changed to remain effective.

There is one other factor to consider when evaluating the effectiveness of this educational campaign. In June 2002, the Hayman fire burned 138,000 acres mostly on the Pike National Forest (17,000 acres were on the Pikes Peak Ranger District); it destroyed 132 homes and came within 20 miles of Colorado Springs (Graham 2003). Although homeowners in the study area were not directly threatened by the Hayman fire, some of the observed change in homeowner attitudes toward wildfire risk may be attributable to this fire. We cannot determine how much of the observed effect on the housing market was due to the educational campaign and how much was due to the Hayman fire. However, given the level of public interest, as demonstrated by the number of hits on the Web site, we believe that a significant portion of the observed changes can be attributed to the program. Furthermore, although the Hayman fire may have increased homebuyers' awareness of wildfire risk and may have encouraged them to use the Web site, it did not provide them with sufficient information to determine the relative wildfire risk of a house. For this reason, it is probably not appropriate to think of the effects of events such as the Hayman Fire as independent of the program. Rather, it is one of a number of factors that may encourage the homebuyer to seek additional information, such as that provided on the Fire Department's Web site. This is borne out by an increase in the hits on the Web site during the fire season.

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