NORTHERN ARIZONA UNIVERSITY
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Does the Estimated Impact of Wildfires Vary with the Housing Price Distribution? A Quantile Regression Approach

Working Paper Series—13-04 | September 2013

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Acknowledgements

We would like to thank participants in a Fulbright-Nehru United States India Educational Foundation sponsored graduate econometrics seminar at the University of Goa for inspiration, The W.A. Franke College of Business for financial support, and Pin Ng for helpful information to develop the methods. All remaining errors are the sole responsibility of the authors.

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1. Introduction

The impacts of wildfires in terms of suppression costs are widely understood, however a relatively small body of research exists investigating the non-market costs of wildfires. One commonly applied method of non-market valuation that can be useful in determining non-market costs of wildfire is the Hedonic Property Model (HPM). Hedonic property models are revealed preference methods of non-market valuation and use house pricing data to estimate implicit prices of environmental hazards or amenities not commonly bought and sold in markets. With hedonic property analysis, a regression is estimated predicting sale price of a home as a function of a set of relevant control variables and the environmental variable of interest (Rosen, 1974). The estimated coefficient on the environmental variable of interest is the “marginal implicit price” of the non-market amenity or hazard. While hedonic property models are relatively common, few hedonic property models investigate the impact of wildfires on house prices, and even fewer use quantile regression techniques.

As described by Koeneker and Hallock (2001), simple OLS assumes a constant marginal impact across the entire distribution of the dependent variable. In contrast, quantile regression estimates a range of marginal impacts for different quantiles of the distribution for the dependent or “response” variable, consequently providing a significantly more “complete picture” of the true impact of the explanatory variable (Koeneker and Hallock, 2001). The study presented uses housing price data for a small geographic set of variables from 1985-2003 in southern California. Several wildfires occur within the geographic area during the sampling period. The aggregate cost of wildfire obtained from HPMs equals the average dollar drop in house prices multiplied by the number of single family houses in the representative population. However, if wildfires have a different impact on house prices for different levels of the house price distribution, aggregate estimates based only on an average implicit price from OLS could be inefficient and potentially ineffective policy tools. We extend the current research on the impacts of wildfire using a quantile hedonic regression. We find the impacts of wildfires to have significant variation over the distribution of house prices, resulting in policy-relevant implications.

2. Previous Research

The HPM is commonly used to model housing markets, and is often used to measure the value of environmental amenities or dis-amenities proximate to the home, including: open space, (Irwin, 2002), water quality (Leggett and Bockstael, 2000), nuclear waste transport (Gawande and Jenkins-Smith, 2001), and maintaining adequate lake water levels (Loomis and Feldman, 2003). Forest-related HPMs include estimating the value of forest fuel reduction in Arizona (Kim and Wells, 2005), and forest proximity and management practices (Kim and Johnson, 2002). Previous research on the effect of wildfires on house prices finds a negative initial impact on house prices. A study by Loomis found that house prices in an unburned community 2 miles from a Colorado wildfire decreased by 15% after the fire (Loomis, 2004). In addition, a study by Price Waterhouse Coopers in New Mexico found that house prices in Los Alamos decreased by 3 to 11% after the Los Alamos wildfire (FEMA, 2004). Only one previous study exists estimating the impact of repeated wildfires on house prices. Mueller et al. (2009) find relatively large impacts of repeated wildfires on house prices over time, with the first fire reducing house prices by 10%, and a second fire reducing house prices by 23%.

An extensive body of research exists estimating hedonic property models using OLS, however, few studies employ quantile regression. Most studies applying quantile regression do find evidence that marginal implicit prices vary across the conditional distribution of house prices. For example, Kuethe and Keeney (2012) investigate the impact of animal agricultural facilities using quantile regression and find that estimated price impacts are not constant as house price varies. Liao and Xizhu (2012) also find evidence of “substantial variation” of the implicit prices of housing characteristics. Finally, Uematsu et al. (2012) find natural amenity is positively related to farmland values, with a greater impact on higher price ranges of farmland. Both wildfire studies assess the effect of a single wildfire on house prices using OLS, and none of the quantile regression analyses estimate the impact of wildfires. Therefore, we contribute to the existing body by assessing the impact of multiple wildfires using quantile regression, allowing a deeper understanding of the impact of repeated wildfires on the distribution of house prices.

3. Model

Hedonic property models infer values of environmental amenities or hazards based on observed housing purchase decisions are thus considered revealed preference methods of non-market valuation. Rosen (1974) first proposed the detailed theoretical construct for the HPM. It is based on the proposition that identical houses in similar neighborhoods will have different prices if the houses have different levels of an environmental amenity or dis-amenity. For example, homebuyers are willing to pay more for a house with an environmental amenity such as being located on a lake, and less for a dis-amenity such as proximity to hazardous waste sites. The resulting house price differential between houses with varying levels of an environmental amenity or dis-amenity is homebuyers’ marginal willingness to pay. In order to determine the marginal implicit price using a hedonic property model, it is thus necessary to control for other characteristics that determine house price, such as structural characteristics, neighborhood demographics, and housing market trends.[1]

In our HPM, the dependent variable is the natural log of the real sale price, adjusted using the housing price index for Los Angeles, Riverside, and Orange Counties (1983 base year). A log-linear specification allows the marginal effect of each independent variable to vary with the level of the dependent variable. Thus, the marginal effects of independent variables change as house price varies. Little theoretical guidance exists on the choice of functional form for HPMs because the predicted hedonic price is the result of the behavior of many different buyers and sellers (Taylor, 2004). Although several alternative specifications are possible, we chose the log-linear specification because it is commonly found in the literature. [2]

To address the temporal effects of wildfires on house prices, a sale date for each house is required. The recorded sale date is not the date when the actual purchase decision was made because offers on house purchases are made one to two months prior to the recorded sale date. Since homebuyers are locked into their contracts once an offer is made, the time element of our model is represented by a decision date, defined as 60 days prior to the recorded sale date. For example, if a sale date is April 30, 1998, the decision date is March 1, 1998. The independent variables of interest are wildfire indicator variables. Controls for housing structure and neighborhood demographics are included. The general model is as follows:

$$P_{it} = f\,(E_{it},\ S_i,\ N_{i,}) \tag{1}$$

Where P_{it}: Sale amount at decision date t, with sale amount deflated using the annual housing price index for Los Angeles, Orange, and Riverside Counties (1983 Base Year), E_{it}: Environmental variables of interest for house *i* at time *t*, $S_{i,}$: Structural characteristics of house *i,* and $N_{i,}$: Neighborhood demographics for house *i.* The choice of included independent variables for our first stage hedonic property model was

[1] See Taylor (2004) and Plamquist (1991) for a comprehensive discussion of the theoretical aspects of hedonic property models.

[2] Further analysis of the functional form specification in the OLS model is available from the authors upon request.

based on prior research, data availability, and data characteristics. The following are the independent variables we chose to include in our empirical specification:

E_{it}: Environmental and Location Variables:

(i) *After One Fire*: An indicator variable that equals one if a house sold after and is located within 1.75 miles of exactly one wildfire

(ii) *After Two Fires:* An indicator variable that equals one if a house sold after and is located within 1.75 miles of exactly two wildfires

(iii) *Days Since Most Recent Fire:* Number of days since the most recent wildfire

(iv) *Distance to USFS Land*: to the edge of the nearest USFS owned land (meters)

(v) *Elevation:* Elevation of the house lot (meters) above sea level

The elevation of a house lot serves as a proxy for vegetation type (higher elevations tend to have more flammable vegetation in southern California). Houses located at higher elevations and nearer to forests have a higher risk of burning from a wildfire.

S_i: Housing Structure Variables:

(i) *Square feet*

(ii) *Year Built*

Several measures of housing characteristics were available. Many of the housing characteristics are highly correlated. When all structural characteristics were included, the model shows signs of collinearity problems. *Square feet* is a commonly used explanatory variable in hedonic property models to control for size of housing structure, and therefore is the structural characteristic we decided to include. We also include *Year Built* as a measure of housing structure quality.

N_i: Neighborhood Demographics Factors:

(i) *Median Household Income*: Median household income in census tract (Year 2000 dollars)

(ii) *Percent with No High School Degree*: Percent of residents in census tract above 18 years old with no high school degree

Neighborhood characteristics commonly included in hedonic models are school district quality and household income (Taylor, 2004). A direct measure of school district quality is unavailable within our data, so a measure of the percent with no high school degree in a neighborhood is used as a proxy for the relative level of educational attainment in a particular community. Neighborhoods with high percentages of educated people generally have higher quality schools. Median household income is also included as a proxy for neighborhood desirability.

General trends in real house prices may occur over time. To reflect these general market trends in the real house prices, we include a daily time trend variable. The empirical model specification is as follows:

$$\begin{gathered} \textit{Log (Real Sale Amount)} = \beta_0 + \beta_1 \textit{*After One Fire} + \beta_2 \textit{*After Two Fires} + \\ \beta_3 \textit{*Days Since Most Recent Fire} + \beta_4 \textit{*Square Feet} + \beta_5 \textit{*Year Built} + \\ \beta_6 \textit{*\% with no High School Degree} + \beta_7 \textit{*Median Household Income} + \\ \beta_8 \textit{*Distance to USFS Land} + \beta_9 \textit{*Elevation} + \beta_{10} \textit{*Trend} \end{gathered} \tag{2}$$

We apply the method of quantile regression described in Koenker and Hallock (2001) using the qreg command in STATA. Qreg estimates the regression using linear programming techniques as described in Armstrong, Frome, and Kung (1979). It also estimates the variance–covariance matrix of the coefficients by using a method proposed by Koenker and Bassett (1982) and Rogers (1993).

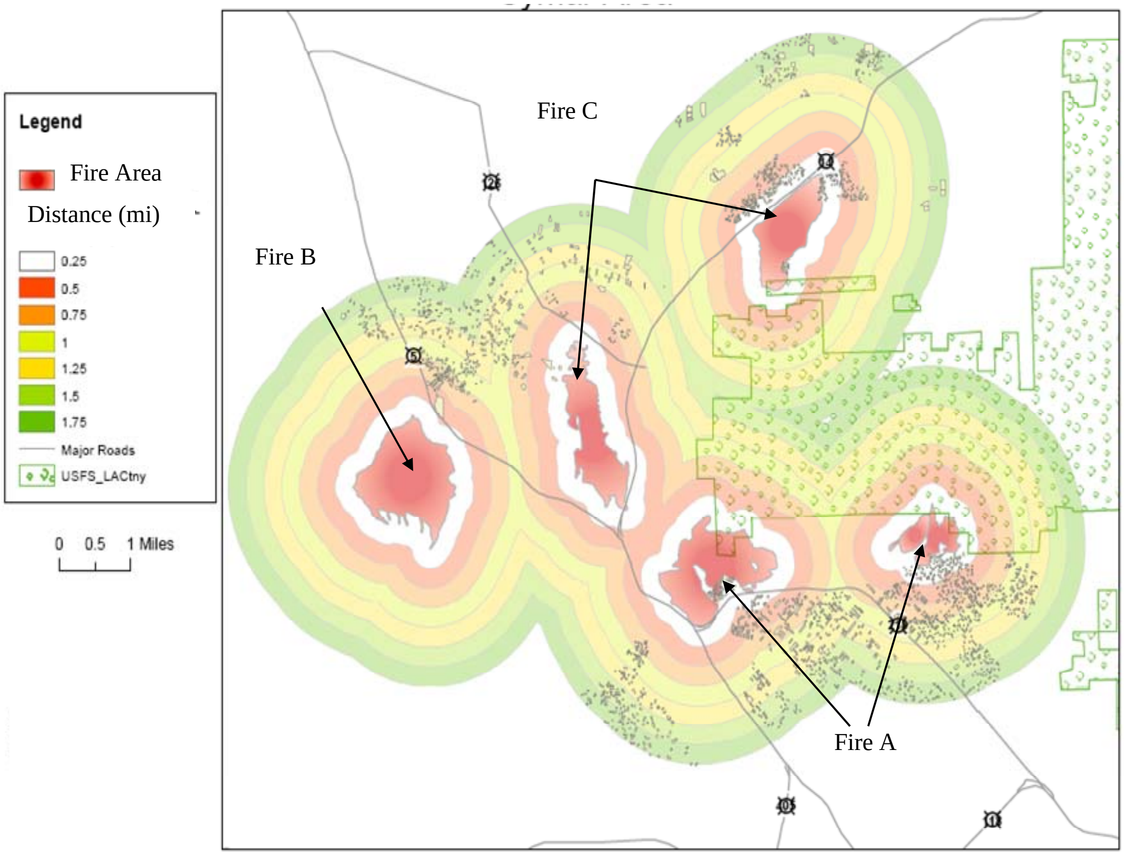
4. Data and Sampling Methodology

We obtained several datasets from various sources and merged them to form a database that includes housing parcel sale date, sale amount, location, demographic characteristics and fire occurrences. Each housing parcel is a single-family residence located within 1.75 miles of a relevant wildfire. All parcels sold at least once between 1989 and 2003. Over 54,000 single-family residences were available to sample from. Outliers were removed from the sample if they were recorded as having less than 500 square feet, if the sale amount in dollars per square foot was less than $50, and if the sale amount appeared to be a data entry error. In addition, houses with zero bedrooms or zero bathrooms were eliminated from the sample. Because we linked housing data with demographic data using a zip code, houses with no recorded zip code were eliminated from the sample. After outliers were removed, the sample was stratified by distance to wildfire and sale date. Each wildfire was mapped with a series of quarter mile rings from the fire center, until the last ring, which is 1.75 miles from the fire center. A target of 25 houses for each distance strata and each year was used. Houses were randomly sampled when there were more than 25 houses for a given distance and sale date.

Our 1.75-mile cut-off is consistent with the distance cutoffs used in previous HPMs related to environmental hazards and dis-amenities. For example, Loomis (2004) measured the effect of a forest fire on house prices in a town located about 2 miles from the fire. Gayer, Hamilton, and Viscusi (2000) use quarter mile distance cutoffs ranging from 0.25 mile to 1 mile in a hedonic study on Superfund sites. In another hedonic study on the impact of oil and natural gas facilities Boxall, Chan, and McMillan (2005) find that oil and sour gas facilities located within 4km (2.48miles) significantly affect house prices. All of the fires modeled in our study are small fires (about 1,000 acres each), and none of them resulted in houses burning to the ground. Based on discussion with U.S. Forest Service fire specialists, the 1.75 mile cut-off chosen also seemed reasonable based on fire risk and other concerns such as evacuation areas.

Wildfires that occurred in the 1990s were chosen for analysis to ensure we have sufficient data after each wildfire to analyze long-term effects. Los Angeles County was selected because there were numerous wildfires within the wildland urban interface in the county during the 1990s. The study area is composed of five fires and is approximately 5.25 miles across. See Figure 1 for a map of the fire area. The darkest areas are the fire perimeters. The gray shaded colored areas represent 0.25-mile rings mapped out from each fire perimeter. The tiny gray shapes represent housing parcels.

Figure 1: Map of Fire Area



The Sylmar Fire occurred on November 25, 1991 and the Polk Fire occurred on November 28, 1991. Because the Sylmar and Polk fires occurred within three days of and just a few miles from each other and are considered one fire (Fire A) for purposes of this analysis. The Towseley fire occurred on December 4, 1995 and is treated as one fire (Fire B). The Placerita Fire occurred on July 3, 1997 and the Sierra Fire occurred on August 8, 1997. Because the Sierra fire occurred less than 40 days after the Placerita fire, also within miles of the Placerita fire, the Placerita and Sierra fires are also counted as one fire (Fire C). All three wildfires are of comparable size—Fire A burned 937 acres, Fire B burned 818 acres, and Fire C burned 977 acres.

Recall that we generated an *After One Fire*, *After Two Fires* and *Days Since Most Recent Fire* variable for each house. Each house in the study area is located within 1.75 miles of at least one of the fires, but may have sold before the nearest fire. A house within our sample is considered to experience a wildfire if it sells after and is located within 1.75 miles of the wildfire. That is, our *After One Fire* variable is equal to one if a house sold after and was located within 1.75 miles of exactly one fire. Alternatively, houses that sold before all fires located within 1.75 miles of the house are coded with *After One Fire* equal to zero and are treated as a control group. Likewise, our After Two Fires variable is equal to one for those houses that sold after and were located within 1.75 miles of exactly two fires.

The parcel data were obtained from Los Angeles County through Nobel Systems. The data contain the geographic location, sale date, sale price, and structural characteristics of housing parcels in Los Angeles County. Sale price data is deflated using an annual Housing Price Index for Los Angeles, Orange, and Riverside Counties. Annual unemployment rates for the state of California were also obtained from the Bureau of Labor Statistics website. The Housing Price index uses 1983 as a base year, so the mean real sale amount for each fire area is in 1983 dollars. The demographic variables are from the 2000 Census, so median household income is measured in year 2000 dollars. Seventy-three percent of the houses sampled are located within 1.75 miles of and sold after at least one wildfire. Fifty percent of the houses sampled are located within 1.75 miles of and sold after at least two wildfires.

5. Results

The results from the quantile regression analysis are presented in Figure 2 as the solid line with the grey area representing 95% confidence intervals. As seen in the graphs, the explanatory variables with the most variation across the distribution of house prices are the *After One Fire* and *After Two Fires* dummy variables, our environmental variables of interest. We therefore choose to focus on the *After Fire* variables in our discussion. [3] As mentioned, our house price data is $152,967 in 1983 dollars. Using information from the current house price index,[4] the mean sale price from our data is equal to approximately $594,048. The estimated coefficients on the *After Fire* variables and t-statistics for three different quantiles are reported in Table 1 converted into 2013 dollars. Note that the estimated coefficients are smaller in absolute value for the lower quantiles relative to the higher quantiles. In fact, the estimated coefficients vary by almost 95% from the 25th quantile relative to the 75th quantile.

Table 1: Estimated Coefficients on After Fire Variables

	Quantile = 0.25	*Quantile = 0.5*	*Quantile = 0.75*
After One Fire	-0.1740	-0.2550	-0.3300
	(8.78)**	(10.26)**	(12.93)**
After Two Fires	-0.1130	-0.2340	-0.3200
	(4.58)**	(7.54)**	(10.04)**

Absolute value of t-statistics in parentheses

* significant at 5% level; ** significant at 1% level

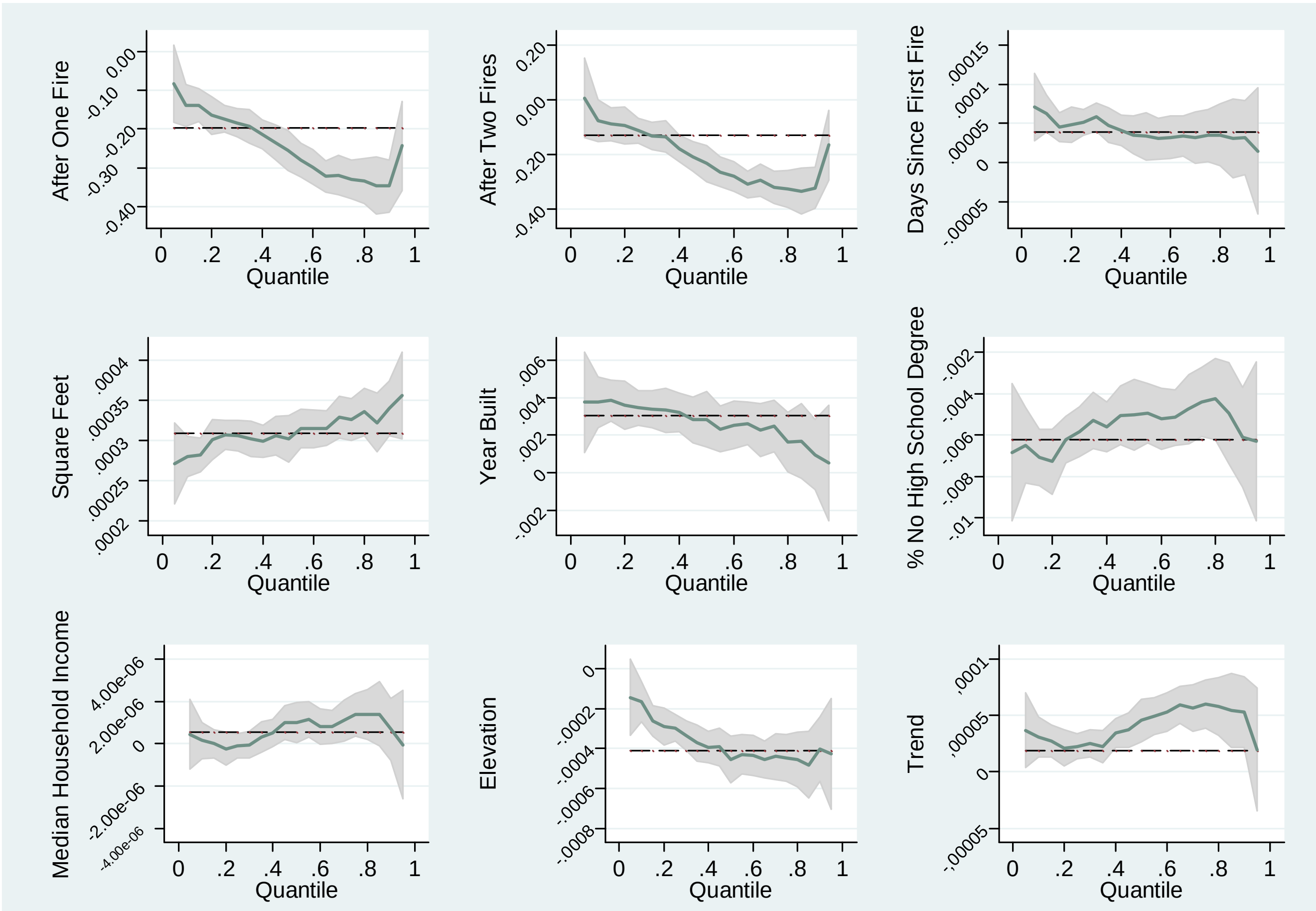
The estimated implicit price in a log-linear hedonic property model is = $\hat{\beta}\bar{y}$. Therefore, to calculate the marginal implicit price in year 2013 dollars, we multiply the estimated coefficients on the dummy variables times $594, 048. The estimated implicit prices for the *After Fire* variables are reported in Table 2. The estimated implicit price of one wildfire is $151,000 using the 50th (median) quantile, and the estimated implicit price of a second wildfire is an additional $139,000. In contrast, the estimated implicit price of one wildfire is $103,000 using the 25th quantile, and the estimated implicit price of a second wildfire is an additional $67,000. Finally, the estimated implicit price of one wildfire is $196,000 using the 75th quantile, and the estimated implicit price of a second wildfire is an additional $190,000. Note the large differences between estimated implicit prices for the 25% quantile versus the 75% quantile. The estimated implicit price of one wildfire is almost $93,000 more in the higher quantile of the distribution, and the estimated implicit price of a second wildfire is nearly $123,000 more in the higher quantile of the distribution.

Table 2: Estimated Implicit Price by Quantile

	Quantile = 0.25	*Quantile = 0.5*	*Quantile = 0.75*
After One Fire	-$103,364	-$151,482	-$196,035
After Two Fires	-$67,127	-$139,007	-$190,095

[3] Please see the appendix for full specification results
[4] http://research.stlouisfed.org/fred2/graph/?s[1][id]=CASTHPI

Figure 2: Quantile Regression Results



Comparison to OLS

Many past hedonic property models use OLS or similar estimation techniques to estimate the marginal implicit price. OLS estimates are formed on a conditional mean, while in contrast the 0.5 quantile is comparable to a median estimate of the coefficient. Table 3 shows the estimated coefficients on the *After Fire* variables from OLS versus the median quantile. OLS estimates are also shown in Figure 2 as the dashed horizontal line. The OLS point estimates are smaller in absolute value relative to the median estimates. However, OLS estimates may over-estimate the impact of wildfires for lower levels of the distribution, and under-estimate the impact of wildfires for higher levels of the house price distribution. Thus, for our dataset, practitioners using OLS without considering the distribution of house prices could under-estimate relative to the median.

Table 3: Estimated Coefficients and Marginal Implicit Prices, OLS vs. Median Quantile

	Estimated Coefficients		Implicit Prices	
	Quantile = 0.5	*OLS*	*Quantile = 0.5*	*OLS*
After One Fire	-0.2550	-0.1972382	-$151,482.26	-$117,168.98
	(10.26)**	(9.94)**		
After Two Fires	-0.2340	-0.12891868	-$139,007.25	-$76,583.90
	(7.54)**	(5.19)**		

6. Discussion and Conclusions

Net Benefits Estimation

When using hedonic property analyses to estimate net benefits or costs, policymakers generally multiply the average estimated implicit price times the number of potential beneficiaries. Approximately 50,000 households exist within our study area. Annualizing the differences in capital value at 5% to make them equivalent to United States Forest Service annual fire-fighting budgets results in differences in predicted costs of $378 Million for one fire with an additional $348M for a second fire using the median quantile. In contrast, predicted costs are as high as $490M for one fire with an additional $475 for a second fire using the 75th quantile. Costs are much lower for the 25th quantile, with predicted costs of $258M for one fire and $167M for a second fire. See Table 4 for a summary of the annualized costs of wildfires by quantile.

Table 4: Annualized Costs of Wildfires By Quantile

	Quantile = 0.25	*Quantile = 0.5*	*Quantile = 0.75*
After One Fire	-258,410,920	-378,705,659	-490,089,676
After Two Fires	-167,818,586	-347,518,134	-475,238,474

Policy Implications

Our results have several relevant policy implications in terms of cost-benefit analysis of wildfire. First, analyses of the impacts of wildfire on house prices using estimators such as OLS predict marginal implicit prices for only the conditional mean of the distribution. While this point estimate is useful, it does not provide policymakers with information about different quantiles of the distribution, and as our data show, the impacts of wildfires change with the distribution of house prices. We find large and economically significant differences in estimated implicit prices and therefore aggregate costs of wildfires for different quantiles of the distribution of house prices. Our results indicate that including estimates using only the conditional mean of the distribution in cost benefit analyses may be inaccurate, and may result in over or under-estimation of net benefits. In addition, our results have implication for researchers and policymakers conducting benefits transfer or applying results from meta-analyses. Previous results from studies that fail to consider differences across quantiles may not be generalizable, especially when the distribution of house prices varies considerably for the area of focus.

While hedonic property analyses are relatively common in the literature, few estimate the impact of repeated wildfires on house prices. Of the studies analyzing the impact of wildfires on house prices, none apply quantile regression technique to investigate how the impact of wildfires on house prices changes across the conditional distribution of house prices. Previous research has found that house prices decrease by as much as 10% after one fire and 23% after a second (Mueller et al., 2009). Our results support existing research in that we also find statistically significant predicted changes in house prices following a first and second fire. Our results contribute to the existing literature because we find that the predicted impacts change significantly over the distribution of house prices, with predicted changes being smaller for lower levels of the distribution and larger for higher levels of the distribution.

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8. Appendix

Table A1: Regression Results

	OLS	*Quantile = 0.25*	*Quantile = 0.5*	*Quantile = 0.75*
After One Fire	-0.197238	-0.17352046	-0.25456213	-0.32991851
	(9.94)**	(8.78)**	(10.26)**	(12.93)**
After Two Fires	-0.128919	-0.1132973	-0.23390544	-0.32032098
	(5.19)**	(4.58)**	(7.54)**	(10.04)**
Days Since First Fire	3.915E-05	0.00005135	0.00003357	0.0000348
	(3.44)**	(4.53)**	(2.36)*	(2.38)*
Square Feet	0.0003098	0.00030757	0.00030238	0.00032635
	(28.56)**	(28.45)**	(22.30)**	(23.40)**
Year Built	0.0030579	0.00346034	0.00284312	0.0024852
	(5.51)**	(6.26)**	(4.10)**	(3.48)**
% No High School Deg	-0.006215	-0.00622776	-0.00502775	-0.00439471
	(9.53)**	(9.58)**	(6.17)**	(5.24)**
Median HH Income	5.5E-07	-0.0000001	0.00000099	0.00000137
	-1.52	-0.27	(2.18)*	(2.92)**
Elevation	-0.00041	-0.00029506	-0.00045428	-0.00044671
	(9.34)**	(6.75)**	(8.28)**	(7.92)**
Trend	1.885E-05	0.00002267	0.00004563	0.00006039
	(2.62)**	(3.16)**	(5.08)**	(6.53)**
Constant	5.9609597	4.87123632	6.39188391	7.16281064
	(5.65)**	(4.63)**	(4.85)**	(5.28)**
Observations	1762	1762	1762	1762

Absolute value of t statistics in parentheses

* significant at 5%; ** significant at 1%