If a Fire Burns in the Forest and It Doesn't Affect the Economy, Does It Even Make a Spark?: An Examination of the Economic Effects of California Forest Fires in the 1990s and 2000s

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Abstract

We construct an original panel data set of counties in California to examine the economic impact of forest fires. We find that there is no statistically significant relationship between forest fire extent and a range of common economic indicators, which is roughly consistent with the literature and economic theory.

1 Introduction

Forest fire and wildfires are unfortunately a common disaster across the globe. The most documented wildfire of 2020 in Australia was described as "apocalyptic" as it raged across huge tracts of the country (World Economic Forum). The flames can ravage entire towns and completely disrupt the local, and national, economy. Climate change has significantly influenced the intensity of natural disasters and therefore making it even more pertinent to study its societal and market impacts. Comparing spatial data from before, and after, helps visualize the economic impact and understand the expanse of impact. As it is difficult to directly measure the impact of natural disasters, by analyzing the economic consequences with established models there is an opportunity for exploratory data analysis to compose fundamental policy proposals.

As indicated by Diaz (2012), the impacts of forest fires are often described in terms of lives threatened, structures and homes lost or damaged, and suppression costs. We attempt to uncover any relationships that may exist between forest fire extent and some common economic indicator variables at the county level by examining forest fires that occurred in California from 1990 to 2010.

The rest of this paper is divided into the following sections: section 2 offers a literature review; section 3 discusses the data we used; section 4 contains a basic visual data exploration, supplemented by the Map Appendix; section 5 summarizes our model; section 6 reports our results, supplemented by the Regression Table Appendix; section 7 contains our discussion; and section 8 offers some concluding remarks.

2 Literature Review

New economics students are traditionally taught of a Broken Window Fallacy, which posits that destructive events are often not beneficial to societies. Yet, there is a sizeable literature that suggest that, in some instances, natural destruction can often clear the way for growth that would have otherwise been prevented. For example, Hornbeck and Keniston (2017) find that the Boston Fire of 1872 burned down old buildings, which cleared the way for new, higher-value properties to be constructed. At the wildfire scale, however, Nielson-Pincus et al. (2013) find that wildfire

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suppression efforts lead to immediate growth, which comes at the expense of increased local economic volatility. In our paper, we examine economic indicators and the yearly and county level to see if such recognized growth and volatilities are discernable at this scale and scope.

Hornbeck and Keskin (2014) calculate the percentage overlap of counties with the Ogallala Aquifer to measure its changing economic impact over time. Similarly, we calculate a weighted percentage overlap of counties with forest fire perimeters to conduct our analysis.

It is important to keep in mind that, regardless of our findings of any economic effects, natural disasters like forest fires still have many significant losers. In fact, the greatest spillover effects of forest fires may be caused by the particulate-filled air they produce. Kochi et al. estimates what these and related health consequences and costs of wildfires might be.

3 Data

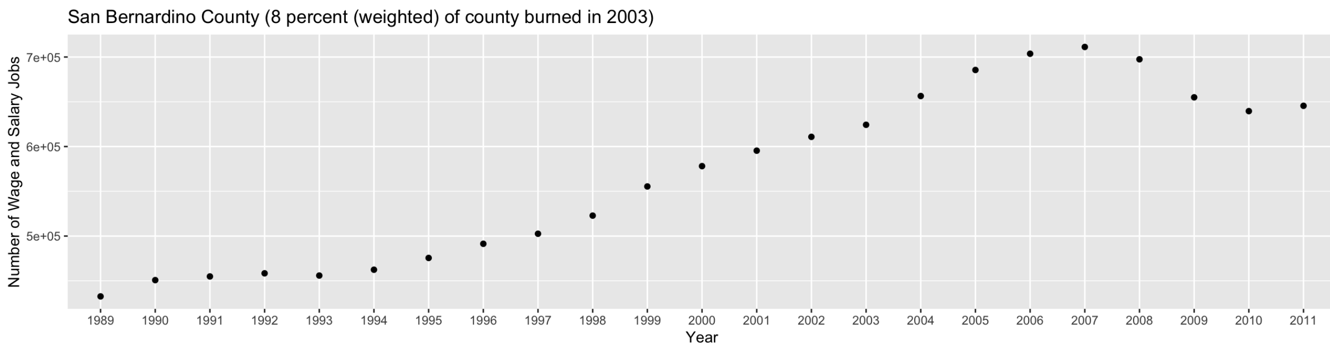
We constructed an original panel data set to attempt to measure the effects of forest fire magnitude on some common economic indicators.

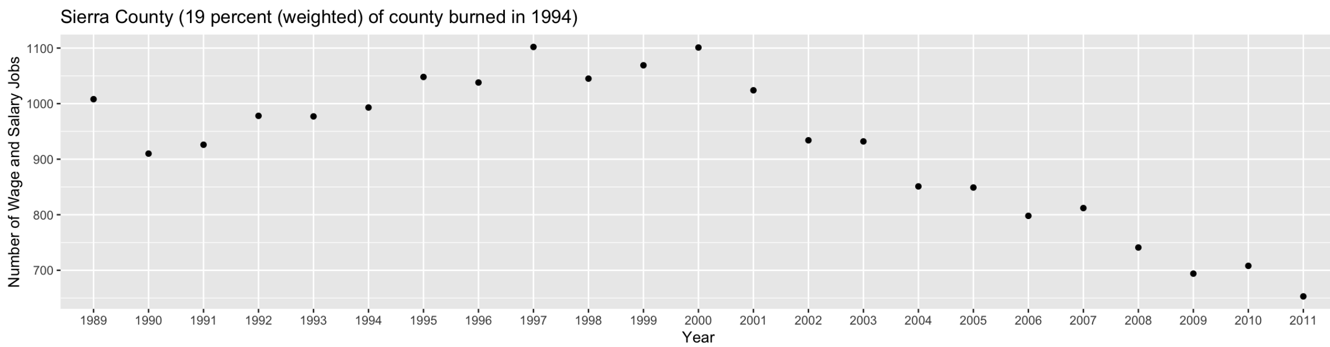
First, we calculated the percentage of each Zip Code Tabulation Area (ZCTA) in California burned by every forest fire from 1990–2010. To do this, we downloaded shape files of forest fire perimeters provided by the California Department of Forestry and Fire Protection and the United States Department of Agriculture Forest Service, along with shape files of ZCTAs provided by the Census. Using QGIS, we calculated the area in the intersection of each fire polygon and ZCTA using the Intersect function and saved these areas in a spreadsheet. Using R, we then divided this intersecting area by the area of each ZCTA to get the percentage burned by each fire. We then computed a weighted percentage burned of each county in California for each year; the weights were based on a ZCTA's population relative to that of the county.

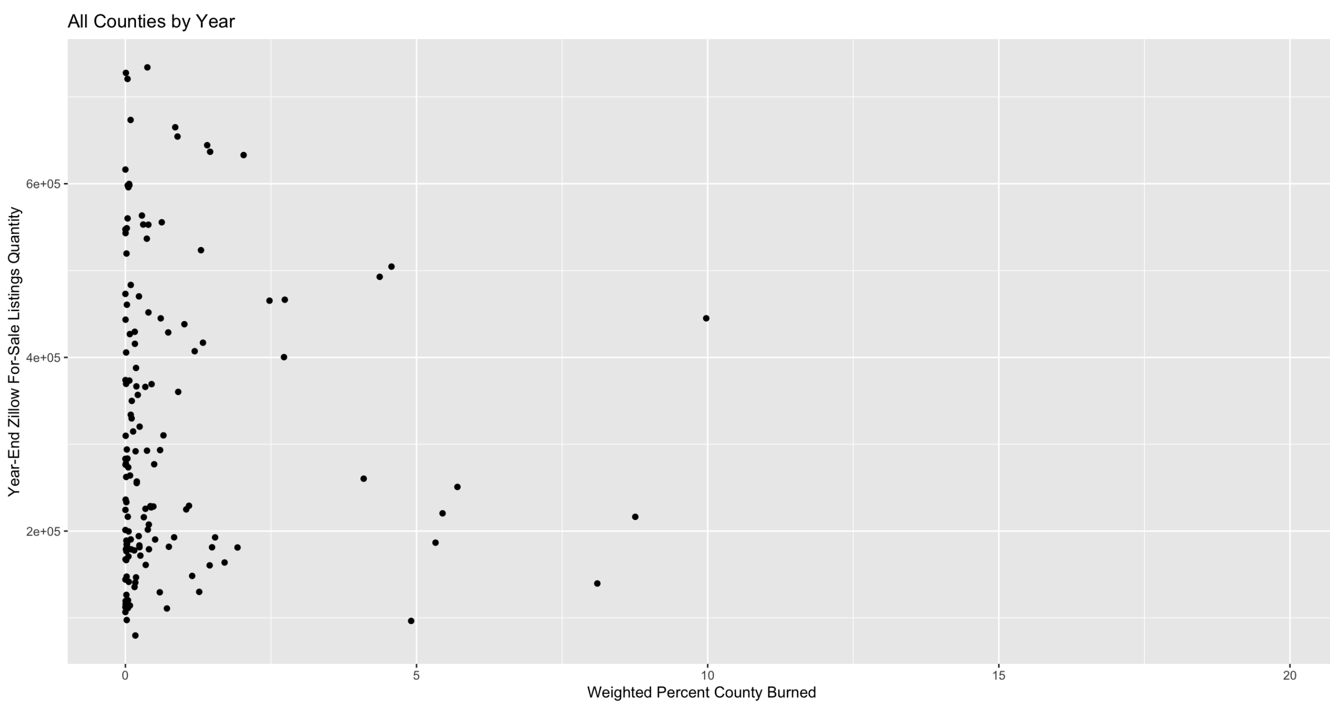
Once we had the population-weighted percentage of each county burned by a forest fire for each year, we added the quantity of housing units listed on Zillow at the end of each year in each county (on December 31) and the yearly economic profile for the counties (CAINC30) provided by the Bureau of Economic Analysis. While the economic profile is provided for each county in each year of our sample, the Zillow data is only available for some counties in more recent years.

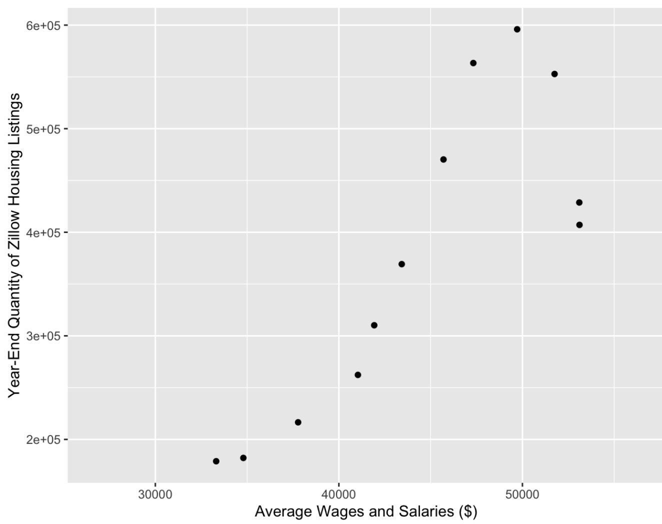
4 Data Exploration

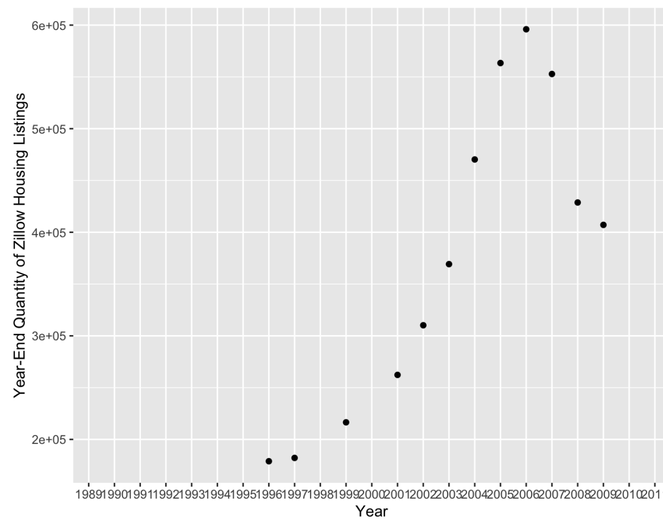
See Map Appendix for a spatial visualization. We can see that the counties that have the highest percentage burned in each fire are also those that are the least populated.

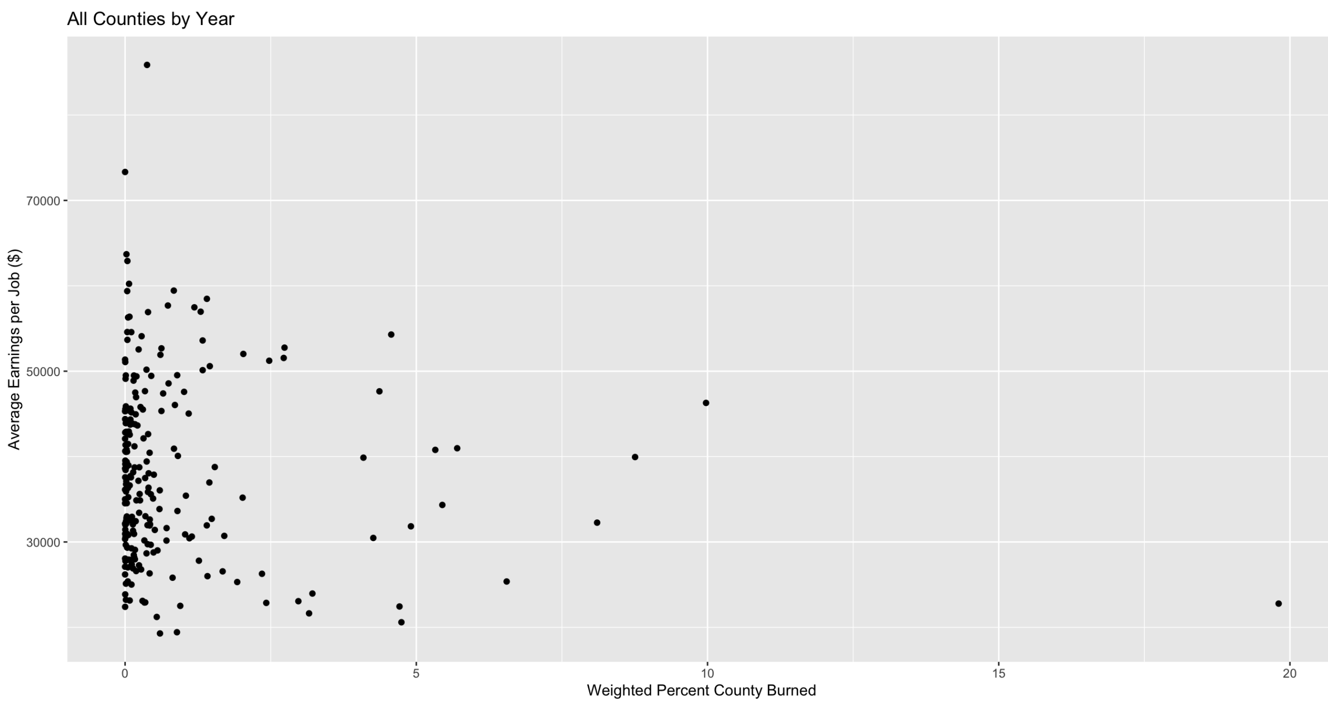












5 Model

We use a standard fixed effects model with year and county fixed effects:

$$Y_{it} = \beta_1 X_{it} + CountyFixedEffects + YearFixedEffects + u_{it}.$$

6 Results

See Regression Table Appendix for detailed results from our models.

The data indicate that there is no discernible, statistically significant relationship between the extent of a forest fire in a county and leading economic indicators that are part of the BEA county economic profile and housing data (Table 2). Below a level of statistical significance, forest fire extent, the fires do seem to have a negative impact on farm proprietors (Table 3). We do, however, observe a couple key relationships. First, for each increase by one day in a fire's length, the weighted percent that the county in which the fire is in increases by a statistically significant amount (Table 1). Second, relationships we would expect based on economic theory generally hold within our panel data (Table 4).

7 Discussion

Our data suggest that there is not a detectable economic impact of forest fires in California. As we can see in the maps in the Map Appendix, this might be because these fires are, by their nature, mostly in the forest, so while there is graphic environmental destruction, the economic impacts at the scope and scale we looked at might not be so extreme. One thing to note is that, for farming, which relies more on the environment than other industries, there is a negative relationship with forest fire extent below a level of statistical significance.

Perhaps if we had more detailed data at the Zip-code level, we might have detected more of an effect. Additionally, In recent years, the BEA has put out an estimate of county-level GDP, which may be useful for similar analyses in the future.

Perhaps damage caused by forest fires and benefits in subsequent growth balance each other out. We are unable to measure this using our data.

It is expected that when the local economy, measured by the average earnings per job, increase, then there will be an increase in economic activity in that area. For example, the creation of more upscale residential buildings. Therefore, the regression analysis of Table 4 is outlining the typical behavior of a growing economy.

8 Conclusions

We do not have sufficient evidence to suggest that the extent of forest fires in California counties have any relationship with the county economic indicators included in the BEA's county economic profile for the year or the available year-end housing present in the Zillow data.

There are clearly areas for future inquiry that include a more detailed examination of forest fires' economic impact at the local level.

9 References

Chaubin et al. (2016) "What is Different About Urbanization in Rich and Poor Countries? Cities in Brazil, China, India and the United States."

Diaz (2012) "Economic Impacts of Wildfire."

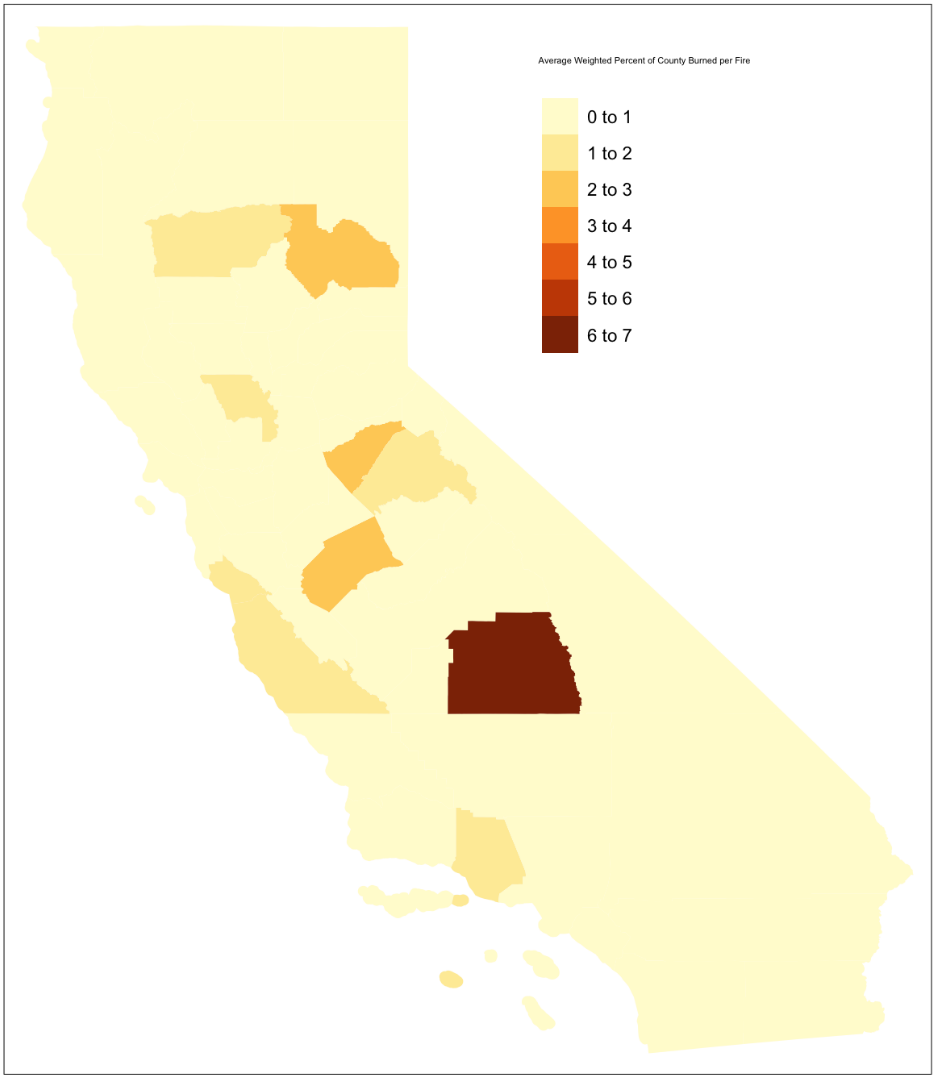
Hornbeck, Keniston (2017) "Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872"

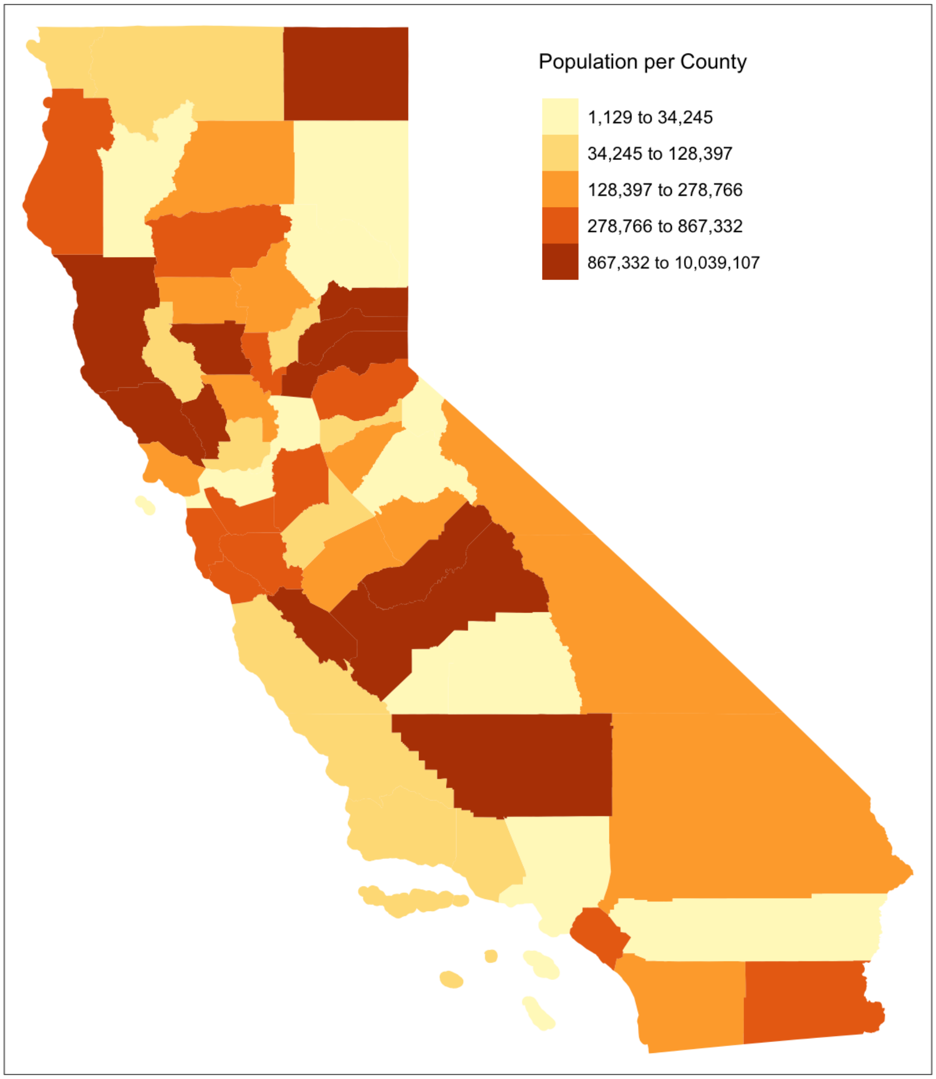
Kochi et al. (2017) "Health and Economic Impact of Wildfires: Literature Review."

Nielsen-Pincus, Moseley, Gerbert (2013) "Job growth and loss across sectors and time in the western US: The impact of large wildfires."

Sheng, Han, Zhou (2016) "Spatially varying patterns of afforestation/reforestation and socio-economic factors in China: a geographically weighted regression approach."

10 Map Appendix




Population per County
1,129 to 34,245
34,245 to 128,397
128,397 to 278,766
278,766 to 867,332
867,332 to 10,039,107

11 Regression Table Appendix

Table 1

	Dependent variable:
	PERCENT_COUNTY_BURNED_WEIGHTED
FIRE_LENGTH_DAYS	0.012***
	(0.003)
Constant	1.730***
	(0.133)
Observations	742
R^2	0.021
Adjusted R^2	0.019
Residual Std. Error	2.920 (df = 740)
F Statistic	15.496*** (df = 1; 740)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: Linear Panel Regression Models of Economic Indicators Against Weighted Percent of County Burned

	Dependent variable:		
	Number of Wage and Salary Jobs	Average Earnings per Job ($)	Year-End Zillow For-Sale Listings Quantity
Weighted Percent Burned per County	1,335.233	27.610	1,522.360
	(1,283.371)	(109.414)	(2,864.315)
Observations	1,334	1,334	148
R^2	0.001	0.0001	0.003
Adjusted R^2	−0.063	−0.064	−0.576
F Statistic	1.082 (df = 1; 1253)	0.064 (df = 1; 1253)	0.282 (df = 1; 93)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3: Linear Panel Regression Models of Farming Economic Indicators Against Forest Fire Extent

	Dependent variable:	
	Number of Farm Proprietor Jobs	Farm Proprietor's Income (Thousands of $)
Weighted Percent Burned per County	−5.272	−939.096
	(9.869)	(2,363.563)
Observations	1,334	1,334
R^2	0.0002	0.0001
Adjusted R^2	−0.064	−0.064
F Statistic (df = 1; 1253)	0.285	0.158
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 4: Linear Panel Regression Models between Economic Indicators and Zillow Housing Data

	Dependent variable:	
	Number of Wage and Salary Jobs	Year-End Zillow For-Sale Listings Quantity
Average Earnings per Job ($)	1.909***	14.274***
	(0.344)	(3.368)
Observations	1,334	148
R^2	0.024	0.162
Adjusted R^2	−0.038	−0.325
F Statistic	30.786*** (df = 1; 1253)	17.958*** (df = 1; 93)
Note:		*p<0.1; **p<0.05; ***p<0.01