The Effect of Wildfires on Labor Markets: A California Case Study

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Abstract

This paper evaluates the impact of wildfires on labor markets via changes in employment levels, total wages, and average wages. I conduct my analysis at the quarter and county level. I stratify labor market outcomes on aggregate, federal government, state government, local government, and private establishment levels. The results of both models indicate that wildfires do not affect the labor market outcomes I investigate. These results are partially driven by data and model limitations. Further research is necessary to investigate the relationship between wildfires and economic outcomes.

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I Introduction

From 2000 to 2017, nearly 2,000 wildfires burned in California. The impact of wildfires on humans and the environment will likely increase in the coming decades due to climate change and the expanding wildland-urban interface (WUI), which is the region where developed and undeveloped land meet (Gibbons et al. 2012, Westerling and Bryant 2008). Despite the increasing impact of wildfires on humans, not just via the destruction of property, but also through the loss of life and smoke pollution, little economic research has focused on the changes in the lives of humans. Instead, much of the literature focuses on risk management and optimization of resource allocation, for example by conducting a cost-benefit analysis on spending on fire repression vs. prescribed burning (see meta analysis by Montagné-Huck and Brunette 2018). Given that California is the most populous state and is both the largest economy in the United State and the fifth largest economy in the world (Associated Press 2018), understanding how climate change will impact the state via wildfires is critical.

In a study of the effects of wildfire smoke on labor outcomes, the authors state that "The expected direct effect of wildfires on labor market outcomes is ambiguous" (Borgschulte et al. 2018). Wildfires can decrease business activities by creating hazardous air conditions and decreasing the demand for tourism. On the other hand, wildfires may temporarily increase local economic activity via suppression and rebuilding (Borgschulte et al. 2018, Nielsen-Pincus et al. 2013). In this paper, I attempt to shed light on the ambiguity of the economic impact of wildfires on local economies.

I focus my analysis on recent decades by limiting my study to the years 2000-2017. I utilize wildfire data from the California Department of Forestry and Fire Protection (CAL FIRE) and labor market data from the Bureau of Labor Statistic's Quarterly Census of Employment and Statistics (QCEW). The main outcome variables I investigate are employment levels, total wages, and average wages for a given quarter and county. In addition to examining these outcome variables on the aggregate level, I also stratify the analysis by whether the data is for publicly owned establishments (Federal, State, and Local Governments) or privately owned establishments. I employ a fixed effects regression and an event study regression model. The results from both of these models suggest that there is no statistically significant impact of wildfires on employment levels, total wages, or average wages.

Section II of this paper starts with a discussion of wildfire trends in California and concludes with a brief literature review of wildfire and natural disaster economic research. Section III discusses the data in greater detail. Section IV describes my methodology. Section V lists ideas for future research and Section IV concludes.

II Background Literature

II.1 Wildfires in California: Background and Statistics

While individual wildfires or even general trends cannot be attributed directly to climate change, research suggests that wildfires are becoming larger, more frequent, and more severe (Miller et al. 2012, Stephens et al. 2013, North et al. 2015). As a result of climate change, California is likely to experience reduced snowpack, less aggregate precipitation, earlier snowmelts, and higher temperatures, which in turn decrease moisture levels and increase the flammability of fire fuel (Westerling and Bryant 2008, McKenzie et al. 2004).

The wildfire risks associated with climate change are exacerbated by increased construction in the WUI. In the two decades since 1990, the developed land area and number of houses in the United State's WUI increased by 33% and 41%, respectively (Radeloff et al. 2018) This growth has been particularly pronounced in California, which has the highest number of homes in the WUI (Radeloff et al. 2005). The higher number of homes in the WUI translates to a higher loss of structures: from 1960-1989, the top 25 most destructive UWI fires in California history destroyed approximately 2000 buildings (Stephens et al. 2009). From 1990-1999, this number rose to over 6000, and from 2000-2007, the number rose further to nearly 8,000 (Stephens et al. 2009). The structure loss has continued to climb dramatically: 10 out of the 20 most destructive fires in California's history occurred from 2015 to 2018 (CAL FIRE 2019). The 2018 Camp Fire and the 2017 Tubbs Fire alone destroyed 18,804 and 5,636 structures, respectively (CAL FIRE 2019). Given that development in the WUI frequently occurs in areas that are already at an elevated fire risk (Fried et al. 2004) and humans are the leading cause of fires in the WUI (Radeloff et al. 2018), WUI development poses important social, economic, ecological, and policy issues (Moritz and Stephens 2006).

In addition to climate change and growth in the WUI, wildfire management has become more complex (Stephens 2019, p115). Funding levels have not kept up with the growing need for prevention, preparedness, suppression that the growth of the WUI and climate change factors merit (Gorte 2018). On the federal level, the Forest Service and Department of the Interior manage wildfires (Hoover 2018). The funding for these agencies' fire management activities has declined by 8% from fiscal year 2017 to 2018 (Hoover 2018). Given that 2017 and 2018 were particularly severe fire seasons[1], this decrease in funding is concerning. The federal government owns 58% of California's forest lands, which means that federal funding is crucial for effective wildfire management (Forest Management Task Force 2019).

[1] Eight out of twenty of California's most destructive wildfires occurred in 2017 and 2018 (CAL FIRE 2019). It is important to note that FY 2017 had the highest appropriation amount since FY 2008 (Hoover 2018). The concern is not the absolute amount of funding, but the funding relative to increased frequency and severity of wildfires.

In addition to lack of funding, effective wildfire management may also be hampered by air quality and environmental legislation. Prescribed burns are fires intentionally set under carefully planned conditions in order to accomplish goals such as decreasing severity of wildfires and restoring ecosystems (Fernandes and Botelho 2003). These controlled burns are a key wildfire management technique. As population in the WUI grows, more prescribed burns are subject to stringent regulation due to the human health protection set forth by the Clean Air Act of 1977 (Stephens 2019, p115). Along these same lines, the National Environmental Policy Act (NEPA) includes procedural requirements that the Forest Service considers a hindrance to effective management (Steelman and Burke 2006). In other words, not only are more individuals living in these areas, but their presence may indirectly increase the likelihood of fires due to these regulations.

II.2 Natural Disaster Economic Literature

A natural starting point to investigate the impact of wildfires on economic outcomes is to survey the literature on other natural disasters. Much of the economic literature surrounding natural disasters focuses on events such as tsunamis, earthquakes, and hurricanes (see e.g. Cavallo et al. 2013). Numerous studies find that wages may increase following natural disasters. The wage increases may be explained by sector-level effects, out-migration, rebuilding activity, and severity of the natural disaster. For example, following a large earthquake in Indonesia, wages of agricultural workers increased because workers shifted from agricultural work to construction work (Kirchberger 2017). Belasen and Polacheck (2008) find that the wages in counties directly affected by hurricanes increase proportional to the size of the hurricane, but that the wages of neighboring counties are adversely affected. They also find that employment fell to varying degrees according to the strength of the hurricane and that there were sectoral employment shifts. The economic literature on other natural disasters provides a helpful perspective on analyzing the impacts of wildfires on labor markets, but separate analysis is still important. Wildfires differ from other natural disasters along the following dimensions:

1. Whereas natural disasters such as hurricanes may only touch ground for at most two or three days, wildfires may burn for weeks or longer (Nielsen Pincus et al. 2013).

2. Wildfires may be focused in more rural, less densely populated areas and thus cause less damage to life and property (Nielsen Pincus et al. 2013). Other natural disasters such as tsunamis and hurricanes may affect densely populated coastal cities and thus have greater economic impacts.

3. Wildfires have important functions in ecosystems and thus can promote and preserve long term environmentally-dependent economic activities such as fishing, tourism and recreation, and logging (Machlis et al. 2002, Butry et al. 2001). Other kinds of ecosystems do not depend on natural disasters to thrive.

4. The primary capital affected by wildfire is timber. In the short run, wildfires may decrease the price of timber by increasing market supply as lumber organizations prematurely cut down trees to save them from the fire (Butry et al. 2001). However, the wildfire decreases the supply of timber in the long run since the inventory stock burned, which increases prices (Prestemon and Holmes 2000). Physical capital such as buildings and machinery that might be destroyed due to hurricanes or earthquakes could have greater impacts on the overall economy, but rebuilding and replacement can occur on a shorter time span than re-growing trees.

5. Because wildfire smoke can spread over large areas, the economic impact of wildfire may be most significant in urban communities affected by smoke rather than in rural communities directly affected by the fire (Borgschulte et al. 2018).

6. Humans have more control over the severity of wildfires than they do over the severity of other natural disasters. Prescribed burns can prevent large wildfires from breaking out by reducing the amount of fuel on the forest ground. Individual humans can exercise caution when they use combustible materials in dry areas, firefighters can combat the spread of wildfire, and city planners can use defensible space to protect property. For other natural disasters, humans can also take preventative action. For example, humans can preserve wetlands in coastal areas to reduce the severity of hurricanes (Constanza et al. 2008) and build earthquake-resistant structures (Skinner et al. 1974). However, humans generally cannot directly *cause* natural disasters other than wildfires[2].

II.3 Wildfire Economic Literature

Much of the economic literature on wildfire as it pertains to human lives focuses solely on health effects[3], the tourism and lumber industries, and suppression costs. Others rely on single-fire case studies and thus may lack external validity.

Hesseln et al. 2003 and 2004 used survey data from Montana, Colorado, and New Mexico and found that wildfires and prescribed burns have a negative effect on the demand for biking and hiking. The decrease in demand could lead to lower wages and employment levels in the tourism industry. However, their analysis suffers from bias: the 2003 study had response rates as low as 30%. The low response rate might indicate that only the people who had the strongest reactions to the survey responded. Butry et al. 2001 found that while wildfires in Florida in 1998 had sizable negative effects on tourism revenues, these effects were not

[2] An exception to this is the practice of hydraulic fracturing ("fracking"), which can increase earthquake risk (Ellsworth 2013).

[3] Though even research here is lacking. In a meta review of the economic costs of adverse health effects from wildfire smoke exposure, the authors only find 1 US-based and 5 internationally-based studies (Kochi et al. 2010). The medical research on wildfire smoke, however, is bountiful (see e.g. Reid 2016 and Liu 2015).

statistically significant.

The most comprehensive studies on the impact of wildfires on labor market are Borgschulte et al. 2018 and Nielsen-Pincus et al. 2013. Borgschulte et al. 2018 find that exposure to wildfire smoke leads to substantial welfare costs by statistically significantly increasing Social Security claims and by reducing earnings and labor participation. They employ nation-wide wildfire smoke data, pollution data, weather data, earnings data, mortality data, labor force status and social security data. Nielsen-Pincus et al. 2013 use BLS QCEW data from 413 western US counties from 2004 to 2008 to estimate the labor market effects of wildfires with high suppression costs. They find that in the quarters during which wildfires occurred, employment and wages rose 1.0 percent and 0.8 percent, respectively and that this increase was driven by "increases in wages in federal and state government counties." They also find that this effect was larger or smaller depending on whether the county specialized in service, government, or nonmetropolitan recreation counties. I further the study of Nielsen-Pincus et al. 2013 by increasing the timespan analyzed, including small wildfires, and by employing two different models.

III Data

The employment and wage data were obtained from the Bureau of Labor Statistics Quarterly Census of Wages and Employment. The dataset contained various employment data such as industry codes, total wages, and employment levels different entities in each county. The QCEW is commonly used in labor market research due to its "high quality, high frequency, timely and historically consistent data on business and employment" (Konigsberg et al. 2005). Belasen and Polacheck (2008) and Nielsen-Pincus et al. (2013) also use QCEW data for their analyses.

The wildfire data comes from the California Department of Forestry and Fire Protection (CAL FIRE) and included the variables: year, responding unit, fire name, alarm date, containment date, cause, reporting agency, acres burned, county FIPS code (unique county identifiers), and county name. CAL FIRE is the most comprehensive source for wildfire data in California. In approximately 500 instances, the number of acres burned by a wildfire in a county reflected not the acreage burned *in that county*, but the overall acreage the wildfire burned. In those instances, I reweighted the acres burned according to the relative size of the counties.

In creating the dataset for my analysis, I combined the QCEW and CAL FIRE Data. The QCEW datasets contained observations for US counties by year, so the first step was to restrict each annual dataset to include only data for California. For the CAL FIRE dataset, I used the alarm date variable to create the quarter variable. Because 25 wildfires did not have an alarm date, they were excluded from the dataset.

Given the high number of included counties that experienced a wildfire (N=2,487) and the fact that the average acreage burned by the excluded wildfires was only 1,403 acres, this exclusion is unlikely to affect the analysis in any statistically meaningful way. I then appended each annual dataset to create a singular dataset containing data from 2000 to 2017. I merged the QCEW and CAL FIRE datasets on the county, year, and quarter variables. I excluded all observations for unidentified counties and restricted the analysis to total employment data across all industries. I created the quarterly employment level variable by averaging the data of the three months in each quarter. The average wages variable is defined as total quarterly wages divided by the quarterly employment level.

III.1 Wildfire Summary Statistics

The smallest wildfire included in the analysis burned 100 acres and the largest burned 501,082 acres. The mean number of acres burned in a county was 4,657 acres, and the median was 536 acres. Of California's 58 counties, only San Francisco County did not experience a wildfire in the sample timeframe. The most wildfires occurred in Kern County, Los Angeles County, and Riverside County. The fewest wildfires occurred in Kings County, Marin County, and San Mateo County (see Figure 1 below). The vast majority of wildfires burned in Quarter 3 (see Appendix Figure 4).

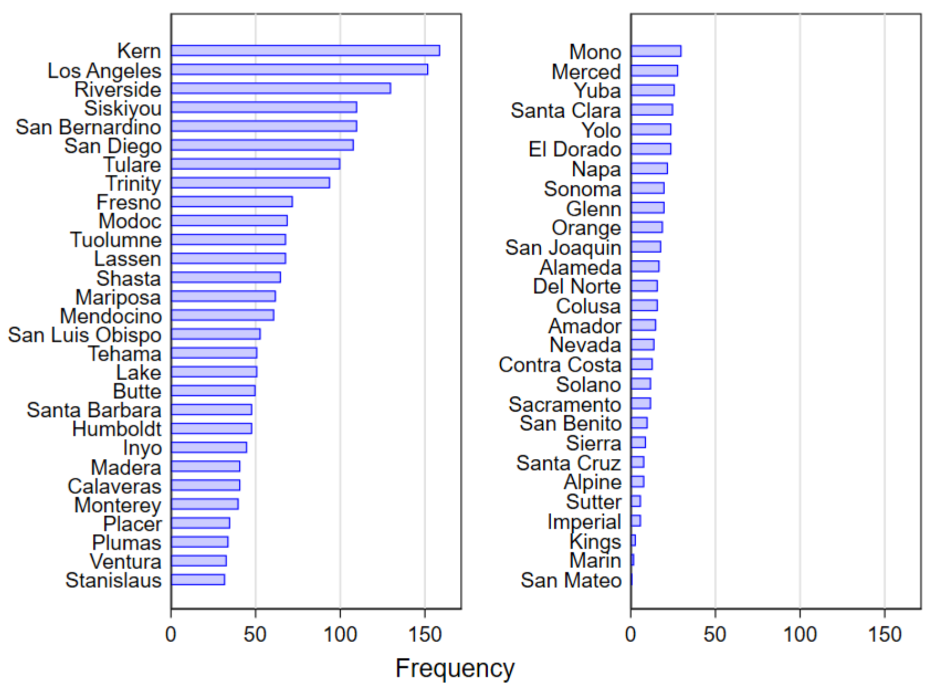

Figure 1: Number of Wildfires in Each County

III.2 Data Limitations

The CAL FIRE dataset did not contain information on the numbers of structures destroyed by individual fires. I found annualized data of structures lost, but this data was not sufficiently granular to be useful to my analysis. The CAL FIRE dataset also did not include any weather information. Weather matters primarily in determining the spread and intensity of fires, and this effect is captured at least partially by the number of acres burned. Nielsen-Pincus et al. find that the main channel through which large wildfires, which they define as wildfires that cost at least $1 million to extinguish, affect wages and employment is via these suppression costs. As with the number of structures lost, suppression cost data were available only on the annual level and for the most destructive fires and thus not sufficiently granular for this analysis.

The QCEW data covers 95% of all jobs in the US, but there are some exclusions (BLS 2016). The QCEW excludes private business owners, non-wage earning individuals who experienced a temporary layoff, and unincorporated self-employed individuals (who make up approximately 2/3 of self-employed individuals and includes a large share of agricultural workers (Hipple 2010)). Most important for this analysis, the QCEW excludes state and federal employees that are employed on a temporarily to combat wildfires and other natural disasters (BLS). Given the limitations of the QCEW data, future research would benefit from drawing employment data from a variety of sources. For example, Borgschulte et. al 2018 employ datasets from the Internal Revenue Service, the Census Bureau, and the Bureau of Economic Analysis in addition to QCEW data.

IV Methodology

In order to estimate the relationship between wildfires, wages, and employment, I use two regression models. The first model is a fixed effects regression based on Borgschulte et al. (2018). The second model is an event study regression based on Almond, Hoynes, and Schanzenbach (2008). One difference between their models and mine is that I do not include controls other than county and time fixed effects. Additionally, I add an interaction term to the event study model to evaluate how the severity of fires affects outcomes.

Future research would benefit from including controls for weather, total suppression costs and suppression costs per capita[4], number of acres burned relative to the size of the county, average wealth in the county, primary economic activity in each county, and among others. Some of these controls are captured at least partially by fixed effects. For example, county fixed effects control for the differences in weather between counties that are fixed over the sample period.

[4]Given that suppression costs are not available for all wildfires, including these controls would come at the cost of reducing the sample size

IV.1 Model 1: Fixed Effects Regression

The first set of regressions capture the relationship between log acres burned and the outcome variable log total employment, log total wages, and log average wages (Y) in a given county (c) and quarter (t). Taking the natural log of the dependent and independent variables helps eliminate the potential of large wages or large wildfires from dominating the effects and accounts for the relative differences between counties.

$$Y_{ct} = \alpha + \beta logAcresBurned_{ct} + \eta_c + \delta_t + \varepsilon_{ct} \tag{1}$$

β describes the relationship between log acres burned and the outcome variables. To control for unobserved variables that vary across county but not over time, I include county fixed effects, η_c. To control for unobserved variables that vary across time but not over counties, I include time fixed effects, δ_t. An assumption this model makes is that the extent of the fire has a degree of randomness. While the risk of fires is increasing, the shock of a single wildfire burning a certain specific amount of acres does include this degree of randomness.

IV.1.1 Model 1 Results

Table 1 shows data across all (i.e. public and private) establishments. The coefficient on all outcome variables is 0, which suggests that a one percent change in the number of acres burned leads to no detectable change in employment levels, total quarterly wages, or average wages for a given county and quarter.. The standard errors on the coefficients are close to zero, which suggests a precise estimation of the zero effect. Results for federal, state, and local government and private establishments can be found in Appendix Tables 3 and 4. The coefficients on all estimates are close to zero, all have small standard errors, and none are statistically significant.

Table 1: Outcomes for All Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
Log Acres Burned	-0.000266	0.000297	0.000563
	(0.00127)	(0.00141)	(0.000866)
Constant	11.15***	20.00***	8.850***
	(0.0291)	(0.0521)	(0.0243)
Observations	1094	1094	1094

Standard errors in parentheses
$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Given that Borgschulte et al. 2018 found statistically significant changes in labor market outcomes from wildfire smoke, these results are surprising. The discrepancy from these results and results from previous wildfire studies suggest that the analysis may suffer from omitted variables and would benefit from the inclusion of more controls.

In a series of robustness checks, I changed aspects of the model. I tested the above regression with a linear-linear and log-linear specification and the majority of the vast majority of coefficients were not statistically significant. In the linear-linear specification, the effect of one increased acre burned led to a decrease of $123.6 in total quarterly wages for state government employees, significant at the 95% level (see Appendix Table 5). In the log-linear specification, log employment levels and log total quarterly wages decreased for local government establishments with statistical significance at the 5% and 10% levels, respectively. However, the coefficients on these estimates were essentially 0 (see Appendix Table 6). By comparing the results from this model to the results of the other models, we increase our certainty that there is no effect of wildfires on labor market outcomes.

When I restricted to analysis to wildfires that burned over 25,000 acres ("Mega Wildfires")[1], most coefficients remained statistically insignificant. A 1% increase in the number of acres burned led to a .0126% increase in the employment level for Federal Government, and a 0.01% decrease in total quarterly wages and 0.01% decrease in average wages for private establishments (see Appendix Tables 7 and 8). In order to further investigate the relationship, I also employ an event study model.

IV.2 Model 2: Event Study Regression

Wildfires may occur in the same geographic area in multiple successive time periods. This makes any clear definition of a pre and post period difficult. In order to address the compounding effects that wildfires can have on local economies, I construct a series of leads and lags from when a wildfire occurred. For this model, I restrict analysis to county-quarters during which at least one wildfire occurred.

The below models capture the trends of outcome variables before and after a wildfire occurs. Equation (2) is useful graphing the coefficients on the leads and lags. By including an interaction term with the period after a wildfire occurs (the "post" period), the regression in Equation (3) helps investigate whether more severe wildfires lead to more drastic economic outcomes. The key assumption for these models is that there

[1] Some sources, particularly the popular press (see e.g. Culver 2018) use the US Forest Service's definition of a mega wildfire as a wildfire that burned more than 100,000 acres. The term emerged in response to the extreme wildfires that are even larger than "large" wildfires in the past (Stephens 2019, p112). I use 10,000ha$\approx$ 25,000 acres burned as the benchmark for a megawildfire to increase statistical relevance of estimates (wildfires > 100,000acres: N=5, wildfires > 25,000acres: N=95

is a degree of randomness to the timing of a wildfire.

$$Y_{ct} = \alpha + \sum_{i=0}^{16} \pi_i(\tau_{ct} = i) + \eta_c + \delta_t + \phi_c * t + \varepsilon_{ct} \tag{2}$$

$$Y_{ct} = \alpha + \sum_{i=0}^{16} \pi_i(\tau_{ct} = i) + \beta \text{Post}_{ft} * logAcresBurned_{fc} + \eta_c + \delta_t + \phi_c * t + \varepsilon_{ct} \tag{3}$$

where Y is log total employment level, log total wages, and log average wages in a given county (c) and quarter (t). The coefficient β in Equation (2) captures the interaction between fire intensity and outcome. τ_{ct} denotes the event quarter, defined so that $\tau = 8$ is the quarter during which a wildfire occurred (the event). This specification includes time periods two years before and after the event. π_i are the coefficients on time dummies, η_c are county fixed effects, δ_t are time-fixed effects, and $\phi_c * t$ controls for county-specific linear time trends.

IV.2.1 Model 2 Results

The Table 2 below shows the coefficients β on the interaction term $Post_{ft} * logAcresBurned_{fc}$ from Equation (3). The majority of the coefficients are statistically significant, but they are all close to 0. This means that larger wildfires do impact labor market outcomes differently, but that the effect is very small. Appendix Tables 9-12 show the outcomes for public and private establishments.

The graphical results from Equation (2) show that there is strong seasonality in employment levels, total wages, and average levels at all levels of analysis (except local average wages, where the cyclical trend is much weaker, see Figure 3). Wages continue their upward trend following wildfires. Aside from seasonal variation, employment levels stay relatively constant. The spike in overall, federal, state, and private employment in wildfire quarters suggests that employment is higher in the third quarter of each year. One potential explanation is that because families take vacations during the summer months, businesses must hire more workers for a certain amount of time. Along these same lines, some local employees (e.g. teachers employed by the county) do not work during the summer months. Some of these employees may seek employment in the private sector. Because there is no divergence in trends between the quarters before and after a wildfire, I cannot conclude that wildfires cause a change in the wage and employment trends. The upward slope of the trends may also suggest that wildfires are more likely to occur in areas that are growing, which is supported by the fact that the WUI is expanding (see Section II.1)

Table 2: Fire Size and Economic Outcomes: All Establishments

	(1) Log Employment	(2) Log Total Wages	(3) Log Average Wages
Post=0 × Log Acres Burned	0	0	0
	(.)	(.)	(.)
Post=9 × Log Acres Burned	0.00135*	0.00492***	0.00358***
	(0.000756)	(0.00101)	(0.000782)
Post=10 × Log Acres Burned	-0.00161*	-0.00333***	-0.00172**
	(0.000938)	(0.00119)	(0.000846)
Post=11 × Log Acres Burned	0.00237***	0.000996	-0.00137**
	(0.000885)	(0.00105)	(0.000692)
Post=12 × Log Acres Burned	0.00165**	0.00159	-0.0000568
	(0.000774)	(0.00106)	(0.000821)
Post=13 × Log Acres Burned	0.00106	0.00371***	0.00265***
	(0.000817)	(0.00111)	(0.000815)
Post=14 × Log Acres Burned	-0.00226**	-0.00378***	-0.00151*
	(0.00105)	(0.00135)	(0.000834)
Post=15 × Log Acres Burned	0.00196*	-0.000668	-0.00263***
	(0.00110)	(0.00136)	(0.000730)
Post=16 × Log Acres Burned	0.00169*	0.00174	0.0000485
	(0.000992)	(0.00125)	(0.000888)
Constant	13.41***	22.65***	9.239***
	(0.0104)	(0.0155)	(0.0103)
Observations	17478	17478	17478

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2 below shows the trends for log employment levels, total wages, and log average wages for all establishments. Figure 3 shows the same trends for federal government, state government, local government, and private establishments.

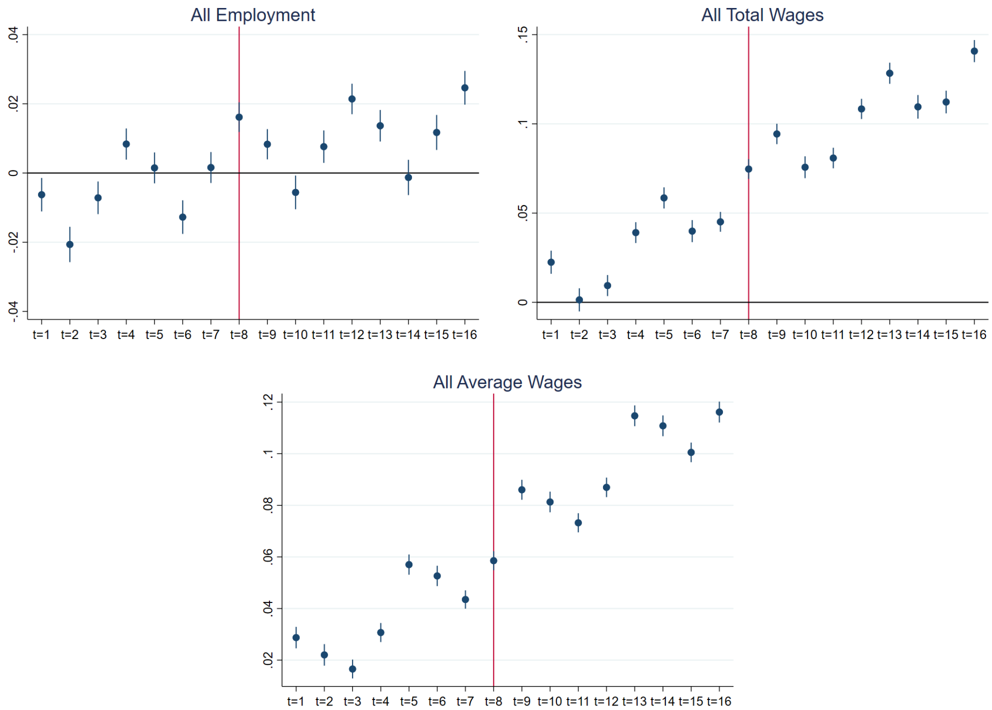

Figure 2: Pictured are the coefficients on Log Employment, Log Total Wages, and Log Average Wages from Equation (3). The red line denotes the time at which the wildfire occurred and the black line serves to illustrate which estimates are statistically significant

Figure 3: Pictured are the coefficients on Log Employment, Log Total Wages, and Log Average Wages from Equation (3) for government and private establishments. The red line denotes the time at which the wildfire occurred and the points above the black line are statistically significant

IV.3 Model Limitations

A threat to identification is the assumption that wildfires are completely randomly assigned to each quarter, year, and county. As discussed in Section II.2, where and when wildfires occur is not random, and neither is their severity. Because the same places tend to have more wildfires (see Figure 1), serial autocorrelation is a concern. In future work, it would be ideal to investigate this more closely and to include more controls for issues of omitted variable bias.

Furthermore, the models do not include any labor market effects caused by smoke. Large wildfires, such as the 2018 Camp Fire, affect regions outside the county as well: the Camp Fire burned in Butte County, but the smoke affected the majority of the State of California. Appendix Figure 5 shows the Air Quality Index, which measures pollution levels based on air pollutants such as particulate matter as specified by the Clean Air Act (EPA 2016). The colors help specify which populations are most likely to experience adverse health impacts from the levels of pollution. AQI levels of 201-300 (purple) and 301-500 (maroon) indicate that most people will be impacted. The high AQI levels compelled multiple universities, including but not limited to UC Berkeley, UC Davis, and Stanford, to close campuses (Svrluga 2018, Brock 2018). The Camp Fire is an outlier: it was the most destructive fire in California's history. Borgschulte et al. 2018 find that smoke negatively impacts labor productivity, labor force earning, and reduces earnings. Neither the analysis by Borgschulte nor the analysis in this paper includes the Camp Fire, and in order to understand the impacts of massive fires such as the Camp Fire, more research is crucial. Ideas for future research are included in the section below.

V Avenues for Future Research

Data and time constraints limit the implications of this research project. The growing size and severity of wildfires merits closer investigation. Avenues for future research include:

- including smoke (AQI) data in the analysis
- identify which kinds of capital are affected in different counties at different times
- stratifying labor market outcome analysis by industry
- including federal workers who are temporarily employed in the county to fight fires
- increasing the number of sources used for employment data
- measuring total employment relative to the size of the population
- measuring the impact of wildfire size relative to county size
- investigating the economic impact of single large fires, for example the Valley Fire (2015), Tubbs Fire (2017), Carr Fire (2018), and Camp Fire (2018)
- comparing economic outcomes following wildfires of the same size that occurred in the same region at different points in time.
- researching potential economic incentive structures to reduce losses from wildfires, for example providing low interest rate loans to allow homeowners to retrofit their houses to reduce vulnerability to fire
- analyzing the the interaction between wildfires, home-loss, out-migration, fire insurance, wealth, and economic outcomes
- identifying the socio-economic implications of wildfires beyond labor market and health outcomes
- investigating changes in local tax revenue due to changes in home values and property taxes

VI Conclusion

Climate change and growth in the WUI are increasing California's wildfire risk. This risk is exacerbated by limited wildfire capacities. Despite the trend of longer fire seasons and larger fires, the economic literature has largely failed to address the economic effects of wildfires.

In this study, I use two models to investigate the effect of wildfires on employment levels, total wages, and average wages. Both models indicate that there is no effect. However, because wildfires do not occur randomly, which means that the models suffer from threat to identification. This identification threat is addressed partially because there is *some* degree of randomness in which county, at what time, and to which extent a wildfire burns. Furthermore, the analysis would benefit from a more comprehensive set of controls to increase confidence in the results. The relationship between wildfires and economic research is ripe for further research.

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VIII Appendix

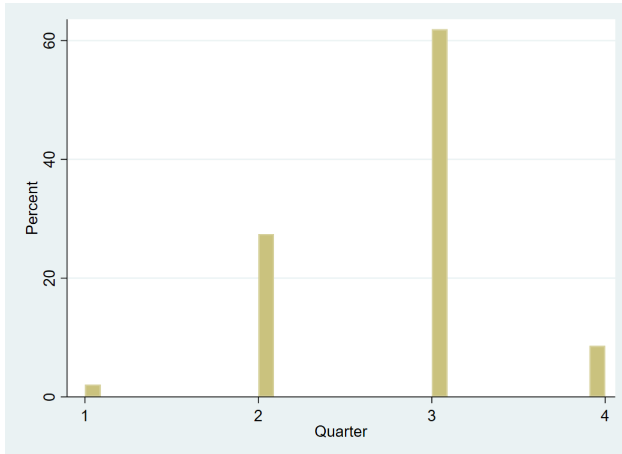

Figure 4: Frequency of wildfires by quarter

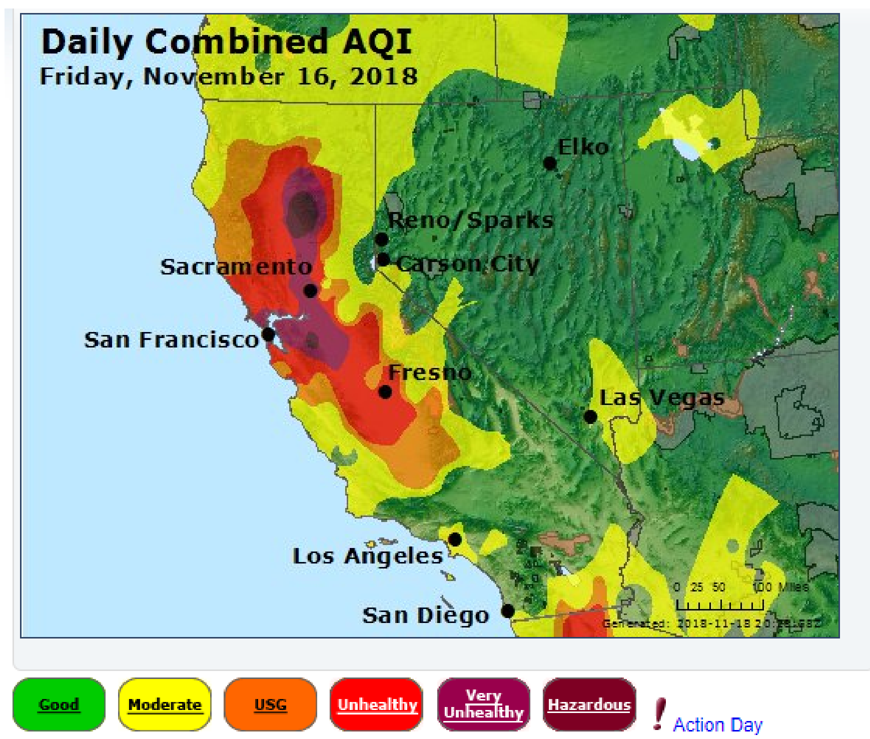

Figure 5: Air Quality Index levels on November 16, 2018. The fire burned primarily in Butte County, but the majority of the State of California was impacted by the smoke the fire caused.

Table 3: Outcomes for Government Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
Panel A. Federal			
Log Acres Burned	0.000705	0.00210	0.00139
	(0.00204)	(0.00280)	(0.00170)
Constant	7.331***	16.54***	9.212***
	(0.0369)	(0.0505)	(0.0265)
Observations	1094	1094	1094
Panel B. State			
Log Acres Burned	-0.00577	-0.00795	-0.00219
	(0.00699)	(0.00733)	(0.00253)
Constant	7.740***	16.93***	9.194***
	(0.170)	(0.203)	(0.125)
Observations	1034	1034	1034
Panel C. Local			
Log Acres Burned	-0.00230	-0.00309	-0.000787
	(0.00159)	(0.00209)	(0.00107)
Constant	9.349***	18.35***	9.000***
	(0.0467)	(0.0503)	(0.0136)
Observations	1042	1042	1042

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Outcomes for Private Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
Log Acres Burned	0.000663	0.00158	0.000915
	(0.00153)	(0.00200)	(0.00132)
Constant	10.85***	19.60***	8.751***
	(0.0324)	(0.0621)	(0.0319)
Observations	1094	1094	1094

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Outcomes for State Government Establishments

	(1) Employment Level	(2) Total Quarterly Wages	(3) Average Wages
Acres Burned	-0.000206	-123.6**	-0.00150
	(0.00160)	(49.67)	(0.00152)
Constant	6505.7***	74030823.6***	9845.6***
	(383.1)	(13979913.5)	(205.2)
Observations	4068	4068	3821

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Outcomes for Local Government Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
Acres Burned	-0.000000231**	-0.000000182^{+}	4.96e-08
	(0.000000105)	(0.000000105)	(3.61e-08)
Constant	9.099***	18.11***	9.016***
	(0.0194)	(0.0205)	(0.00809)
Observations	3910	3910	3910

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Mega Wildfire: Outcomes for Federal Government Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
log_mega	0.0126^{+}	0.0125	-0.000165
	(0.00745)	(0.00848)	(0.00645)
Constant	7.414***	16.72***	9.309***
	(0.124)	(0.0897)	(0.0913)
Observations	196	196	196

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Mega Wildfire: Outcomes for Private Establishments

	(1) Log Employment Level	(2) Log Total Quarterly Wages	(3) Log Average Wages
log_mega	-0.00285	-0.0119**	-0.00901***
	(0.00408)	(0.00550)	(0.00302)
Constant	11.08***	19.95***	8.877***
	(0.0435)	(0.0596)	(0.0358)
Observations	196	196	196

Standard errors in parentheses

$^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Fire Size and Economic Outcomes: Federal Government

	(1) Log Employment	(2) Log Total Wages	(3) Log Average Wages
Post=0 × Log Acres Burned	0	0	0
	(.)	(.)	(.)
Post=9 × Log Acres Burned	0.000334	-0.000912	-0.00125
	(0.00162)	(0.00240)	(0.00146)
Post=10 × Log Acres Burned	-0.00586***	-0.00904***	-0.00318**
	(0.00180)	(0.00244)	(0.00138)
Post=11 × Log Acres Burned	0.00411**	-0.000845	-0.00496***
	(0.00206)	(0.00252)	(0.00142)
Post=12 × Log Acres Burned	0.0114***	0.0148***	0.00337*
	(0.00197)	(0.00298)	(0.00176)
Post=13 × Log Acres Burned	0.00219	-0.000920	-0.00311**
	(0.00184)	(0.00250)	(0.00152)
Post=14 × Log Acres Burned	-0.00610***	-0.00938***	-0.00328**
	(0.00229)	(0.00278)	(0.00136)
Post=15 × Log Acres Burned	0.00408*	-0.00447	-0.00855***
	(0.00246)	(0.00282)	(0.00162)
Post=16 × Log Acres Burned	0.0148***	0.0184***	0.00364*
	(0.00245)	(0.00301)	(0.00189)
Constant	9.417***	18.80***	9.387***
	(0.0232)	(0.0260)	(0.0136)
Observations	17478	17478	17478

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Fire Size and Economic Outcomes: State Government

	(1) Log Employment	(2) Log Total Wages	(3) Log Average Wages
Post=0 × Log Acres Burned	0 (.)	0 (.)	0 (.)
Post=9 × Log Acres Burned	0.00210 (0.00465)	0.00416 (0.00493)	0.00206 (0.00188)
Post=10 × Log Acres Burned	-0.00233 (0.00418)	0.000634 (0.00426)	0.00297* (0.00168)
Post=11 × Log Acres Burned	-0.00374 (0.00454)	-0.00777* (0.00445)	-0.00403** (0.00175)
Post=12 × Log Acres Burned	-0.00204 (0.00469)	-0.00432 (0.00487)	-0.00228 (0.00178)
Post=13 × Log Acres Burned	-0.00101 (0.00468)	0.000576 (0.00466)	0.00158 (0.00183)
Post=14 × Log Acres Burned	0.00277 (0.00503)	0.000190 (0.00490)	-0.00258 (0.00189)
Post=15 × Log Acres Burned	0.00894* (0.00535)	0.00237 (0.00540)	-0.00657*** (0.00195)
Post=16 × Log Acres Burned	0.00495 (0.00560)	0.00199 (0.00578)	-0.00295 (0.00191)
Constant	10.63*** (0.0519)	20.06*** (0.0406)	9.432*** (0.0408)
Observations	16518	16518	16518

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Fire Size and Economic Outcomes: Local Government

	(1) Log Employment	(2) Log Total Wages	(3) Log Average Wages
Post=0 × Log Acres Burned	0	0	0
	(.)	(.)	(.)
Post=9 × Log Acres Burned	0.00389***	0.00518***	0.00129
	(0.00128)	(0.00150)	(0.000868)
Post=10 × Log Acres Burned	0.00173*	0.00176	0.0000221
	(0.000888)	(0.00125)	(0.000848)
Post=11 × Log Acres Burned	0.00386***	0.00505***	0.00119
	(0.00120)	(0.00149)	(0.000805)
Post=12 × Log Acres Burned	-0.00845***	-0.00825***	0.000195
	(0.00147)	(0.00169)	(0.000854)
Post=13 × Log Acres Burned	0.00386***	0.00524***	0.00139
	(0.00140)	(0.00165)	(0.000860)
Post=14 × Log Acres Burned	0.00106	0.00150	0.000446
	(0.00100)	(0.00138)	(0.000929)
Post=15 × Log Acres Burned	0.00260*	0.00275	0.000148
	(0.00139)	(0.00175)	(0.000915)
Post=16 × Log Acres Burned	-0.00881***	-0.00791***	0.000899
	(0.00157)	(0.00183)	(0.000965)
Constant	10.98***	20.31***	9.328***
	(0.0211)	(0.0269)	(0.0113)
Observations	16670	16670	16670

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Fire Size and Economic Outcomes: Private

	(1) Log Employment	(2) Log Total Wages	(3) Log Average Wages
Post=0 × Log Acres Burned	0	0	0
	(.)	(.)	(.)
Post=9 × Log Acres Burned	0.00165	0.00648***	0.00483***
	(0.00108)	(0.00130)	(0.00102)
Post=10 × Log Acres Burned	-0.00191	-0.00422***	-0.00231**
	(0.00128)	(0.00158)	(0.00113)
Post=11 × Log Acres Burned	0.00247**	0.00104	-0.00143
	(0.00120)	(0.00140)	(0.000939)
Post=12 × Log Acres Burned	0.00377***	0.00322**	-0.000547
	(0.00109)	(0.00135)	(0.00102)
Post=13 × Log Acres Burned	0.000981	0.00481***	0.00383***
	(0.00109)	(0.00139)	(0.00106)
Post=14 × Log Acres Burned	-0.00286**	-0.00487***	-0.00202*
	(0.00140)	(0.00176)	(0.00110)
Post=15 × Log Acres Burned	0.00198	-0.000433	-0.00242**
	(0.00148)	(0.00179)	(0.000966)
Post=16 × Log Acres Burned	0.00356***	0.00264	-0.000919
	(0.00138)	(0.00164)	(0.00109)
Constant	13.25***	22.46***	9.207***
	(0.0143)	(0.0196)	(0.0121)
Observations	17476	17476	17476

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$