Estimating the Economic Impacts of Wildfires on County GDP Growth in the US

Jayden Jiangyu Peng

A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Bachelor of Arts, Honours
in the Department of Economics
University of Victoria
April 2020

Supervised by Dr. Felix Pretis
For
Dr. Elisabeth Gugl, Honours Co-Advisor
Dr. Graham Voss, Honours Co-Advisor

Abstract

In this paper, I estimate the economic effects wildfire occurrence (fire location) and magnitude (fire duration) have on economic activities in the United States. While the vast majority of the existing wildfire literature adopts measured state-level GDP data, I use the county-level GDP data newly released by the U.S. Bureau of Economic Analysis (BEA). This is the first release of GDP data on county level, and its availability likely increases the accuracy of measurement as it provides a higher spatial resolution than the conventional measured state-level GDP data. In the empirical models, per-capita real gross county product (GCP) growth is a function of wildfire occurrence and fire duration days. Counties experienced large wildfires are expected to see a decline in GCP growth. Since wildfire occurrence and magnitude are potentially endogenous to economic activities, I use instrumental variable (IV) methods to provide consistent estimates of the effects. One plausible IV for wildfire occurrence is lightning strikes; one plausible IV for fire duration is annual mean of daily precipitation. I find statistically significant evidence that fire duration adversely impacts per capita real GCP growth, but the effect is practically marginal. Statistically, I did not find evidence that fire occurrence affects the per capita real GCP growth due to weak instrument problem.

Acknowledgements:

I would like to thank my honours advisors, Dr. Graham Voss and Dr. Elisabeth Gugl, for their support and revisions. I would also like to thank my supervisor Dr. Felix Pretis for providing help and encouragement since the beginning. I would like to thank Miss. Sheri Liu and her husband Mr. Jon Duan for their help. And finally, I want to thank the 2020 Honours Cohort for being an amazing company.

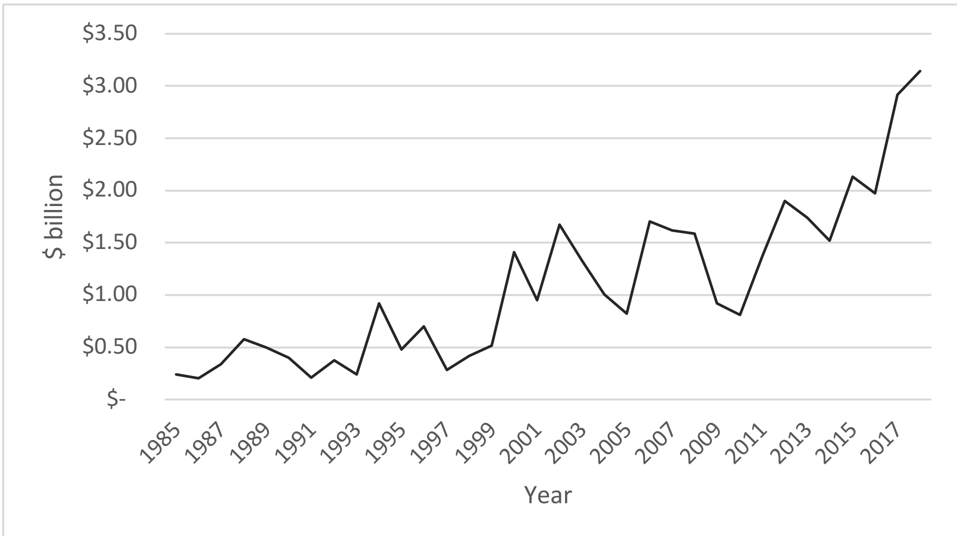
1 Introduction

According to the report of *Suppression Costs (1985-2018)* from National Interagency Fire Center (NIFC, n.d.), Catastrophic wildfires in the US have been driving up the wildfire suppression costs in the past few decades. The Colorado's 2002 Hayman Fire that burned an area of 55,846.6 hectares led to a cost of $115.9 million, which includes $38.7 million in insured private property and $34 million in timber value (USFS, 2013).

As a contribution to understanding the costs, this paper estimates the impacts wildfires have on per capita real output growth in US counties. I hypothesize that experiencing large wildfires adversely impacts the economic growth on a county level.

Throughout the last four decades, the average size of wildfires in the United States has increased from 11 hectares to 43 hectares per fire (Figure Appendix.1), but the number of wildfires has dropped by 40% (Figure Appendix.2) (NIFC – Total Wildland Fires and Acres, n.d.). Most of the increase in average size was driven by the increased number of catastrophic wildfires (Wood, 2015), which not only are harder and more expensive to fight but also causes more damage. For only fire suppression, the Federal Firefighting spent around $0.24 billion in 1985 but more than $3 billion in 2018 (NIFC – Suppression Cost, n.d.). After adjusting for inflation using the CPI for all urban consumers (U.S. Bureau of Labor Statistics), the cost rose more than 5 times. I show in the following plot (Figure 1) how the total fire suppression cost has changed since 1985. The plot presents a clear upward trend for suppression cost with a growing slope.

Figure 1: Total US Fire Suppression Cost ($ billion) (1985 – 2018)



Previous studies do not estimate total economic activities with data that have a higher spatial resolution than state level. The goal of this paper is to bridge this gap in the existing literature by estimating the partial effect of wildfires on real county-level output growth, measured by the newly released US county-level GDP data from the U.S. Bureau of Economic Analysis (BEA). Theoretically, population growth is positively correlated with real output growth, so I control for population growth by using per capita real county output.

In previous literatures regarding wildfires damages, a 2001 paper by Butry et al estimates the costs caused by disastrous wildfires with respect to seven main categories: "presuppression costs, suppression costs, disaster relief expenditures, timber losses, property damage, tourism-related losses, and human health effects." Later studies mostly fall into these categories. For example, using the hedonic price method, Stetler et al (2010) suggest that the view of burned areas reduces property value; Hesseln et al (2003) and Molina et al (2019) suggest the recreation value of burned area is reduced. Also, wildfires lead to shrinking wildlife biodiversity (Soaga et al, 2013).

Many recent studies estimate the economic impacts of wildfires mainly from the path of human health effects. For example, Moeltner et al (2013) conclude that wildfires cause considerable medical expenses. They find that at least several million dollars increase in health costs are caused by wildfires through smoke per fire season in just the Reno/Sparks area of Northern Nevada; they also suggest that together with the cost incurred by close communities in California, several million is just the lower bound. The US health spending per capita in 2013 was $9,129 (CHCF, 2019), so several million dollars could support medical expense of hundreds of people.

Miller et al (2017) find that transport of wildfire smoke significantly contributes to air pollution "for cities hundreds of miles away from the fire itself". They also suggest that exposure to wildfire smoke causes remarkable mortality risk for the elderly. In addition, smoke exposure induces increase in healthcare costs (Miller et al, 2017). Furthermore, Borgschulte et al (2019) estimates the impact wildfire smoke has on labour market through the channel of air pollution. They find that smoke exposure negatively affects labour force participation by decreasing earnings. As a result, the social security payment is increased.

In the second section (Methodology) below, I develop two economic models. In one model, GDP growth is a function of wildfire occurrence and other factors including the first lag of GDP growth, capital growth, technological growth, population growth, the type of main regional economic activity, and regional fire suppression effort. In another model, I use fire duration days, a measure of fire magnitude, to replace wildfire occurrence. In the third section, I present the econometric model and the method used to estimate it. Fourth, I discuss how I obtain and use the datasets for this paper in the data section. Fifth, I report and discuss the results from the estimation. Lastly, in section six, I present my conclusions and discusses some limitations of the paper.

2 Methodology

To estimate the regional economic impact of wildfires, I use county-level GDP as a measure for regional economic activity. I refer to county-level GDP as gross county product (GCP) hereafter. The objective is to see how the GCP growth is affected by wildfire occurrence and magnitude, for which I also have data for the United States on a county basis.

2.1 Endogeneity Problem

Simple regression methods, however, may not provide valid estimates of the effects because of potential endogeneity. Unmeasured contributions to economic activity, such as regional wildfire suppression effort and types of regional economic activity, may also directly affect wildfire occurrence and magnitude. Below, I illustrate the endogeneity problem using my models.

2.2 Model # 1:

Function 1.1:

$$GCP\ Growth_{i,t} = f(GCP\ Growth_{i,t-1}\ , \boldsymbol{Fire_{i,t}}\ , K\ Growth_{i,t},\ Tech\ Growth_{i,t}\ ,$$

$$Pop\ Growth_{i,t}\ , EconType_i\ ,\ Supp_{i,t}\ )$$

Function 1.2:

$$Fire_{i,t} = f(Flash_{i,t}\ ,\ Precip_{i,t}\ ,\ Pop\ Growth_{i,t}\ ,\ EconType_i\ ,\ MaxT_{i,t})$$

- $GCP\ Growth_{i,t}$: GCP growth of county i in year t
- $GCP\ Growth_{i,t-1}$: GCP growth of county i in year $t - 1$
- $Fire_{i,t}$: number of fires in county i during year t
- $K\ Growth_{i,t}$: Capital growth of county i in year t
- $Tech\ Growth_{i,t}$: Technological growth of county i in year t
- $Pop\ Growth_{i,t}$: Regional Population Growth of county i in year t
- $EconType_i$: Type of main regional economic activity of county i– e.g. agriculture, technology
- $Supp_{i,t}$: the regional fire suppression effort of county i in year t
- $Flash_{i,t}$: number of lightning flashes of county i in year t
- $Precip_{i,t}$: annual mean of daily precipitation of county i in year t
- $MaxT_{i,t}$: annual mean of daily maximum air temperature in degrees Celsius of county i in year t

In the first economic model, Function 1.1 shows that GCP growth is a function of a variety of factors: (a) GCP growth in year t should be positively correlated with historical GCP growth. (b) Number of fires would adversely affect GCP growth as my hypothesis suggest. (c) & (d) Higher capital growth and technological growth directly increase output growth. (e) Similarly, Higher population growth means higher labour supply growth, which directly brings higher output growth. (f) Type of regional economic activity could also affect GCP growth rate. For example, Silicon Valley likely has a higher growth on per capita real output than a central US county whose main industry is agriculture. (g) Suppression effort for large wildfires could lead to an economic loss. It could even induce greater economic instability by amplifying seasonal variation in employment in the long run. However, in the short run, it has a positive impact on the local labour market by employment it creates (Moseley et al, 2012).

Function 1.2, on the other hand, shows the determinants of fire occurrence. First, wildfires always start by either natural causes or human-related causes. Natural wildfires are generally started by lightning. Second, high local precipitation would suppress the start of fires, and it would also be helpful in the later stage fire suppression. Third, 84% of wildfires in the US are caused by human (Sean et al, 2019). County population growth contributes to growing local population density, which would likely increase human-caused wildfires. Fourth, comparing to areas focusing on the emerging industries, areas with economic activity such as logging are more likely to have wildfires due to higher fuel stocks. Fifth, as a part of the "fire triangle" (heat, oxygen, and fuel), heat is needed for fires to develop, and high temperature is the main source of heat.

Together the two functions suggest that GCP growth and fire occurrence are jointly determined by factors such as regional population growth, type of main regional economic activity, and potentially other factors. Variables such as $EconType_i$ is not measured in my dataset, so they are left in the error term when I create the regression models. Therefore, the endogeneity problem arises due to the omitted variables. Through the same path, we can see the endogeneity in model 2.

2.3 Model # 2

Function 2.1:

$$GCP\ Growth_{i,t} = f(GCP\ Growth_{i,t-1}\ , \boldsymbol{Dur_{i,t}}\ , K\ Growth_{i,t},\ Tech\ Growth_{i,t}\ ,$$
$$Pop\ Growth_{i,t}\ , EconType_i\ ,\ Supp_{i,t}\ )$$

Function 2.2:

$$Dur_{i,t} = f(Precip_{i,t}\ ,\ Pop\ Growth_{i,t}\ ,\ EconType_i\ ,\ MaxT_{i,\mathrm{t}}\ , Supp_{i,t})$$

- $GCP\ Growth_{i,t}$: GCP growth of county i in year t
- $GCP\ Growth_{i,t-1}$: GCP growth of county i in year $t - 1$
- $Dur_{i,t}$: number of fire days in county i in year t
- $K\ Growth_{i,t}$: Capital growth of county i in year t
- $Tech\ Growth_{i,t}$: Technological growth of county i in year t
- $Pop\ Growth_{i,t}$: Regional Population Growth of county i in year t
- $EconType_i$: Type of main regional economic activity of county i– e.g. agriculture, technology
- $Supp_{i,t}$: the regional fire suppression effort of county i in year t
- $Precip_{i,t}$: annual mean of daily precipitation of county i in year t
- $MaxT_{i,t}$: annual mean of daily maximum air temperature in degrees Celsius of county i in year t

In Function 2.1, I include $Dur_{i,t}$ (the number of fire days) because longer fire duration could lead to greater suppression cost and, on the other hand, higher short-term local employment. Other factors are the same as in Function 1.1.

In Function 2.2, $Dur_{i,t}$ is not determined by lightning strikes, but it is determined by fire suppression effort. Intuitively, greater suppression effort would shrink the fire duration days. Other factors are the same as in Function 1.2.

Analogously, these two functions suggest that GCP growth and fire magnitude are jointly determined by factors such as regional population growth, type of regional economic activity, the fire suppression effort, and potentially other factors. Unmeasured variables such as $EconType_i$ and $Supp_{i,t}$ are left in the error term, and the omitted variables cause endogeneity problem.

3 IV Method

To address the endogeneity problem, I use instrumental variables. Instrumental variable methods require instruments to model exogenous variation in wildfire occurrence or magnitude (or both). In the current context, two plausible instruments are the number of local lightning strikes and the annual mean of local daily precipitation for $Fire_{i,t}$ and $Dur_{i,t}$ respectively. The crucial characteristic potential instruments share is that they likely have no or little effect on economic activity except through wildfire occurrence or magnitude.

**annual mean of local daily precipitation*

In a recent study estimating the long-term impact of climate change on economic activity, using a panel dataset of 174 countries over the years 1960 to 2014, Kahn et al (2019) suggests that persistent changes in temperatures have statistically significant negative impacts on per-capita real output growth. However, statistically, they do not find significant effects for changes in precipitation. Based on this study, I choose to use the annual mean of local daily precipitation as an instrument for fire duration days.

** number of local lightning strikes*

Cloud-to-ground lightning strikes may cause direct damage on various business by interrupting the economic activities especially those that take place outdoors; for example, profits could be easily lost at oil or liquid natural gas terminals due to a large-scale lighting strike. These lightning strikes, however, could be prevented in advance since there are usually signs before they happen. For example, dark and cloudy sky could be a sign for outdoor employees to stay in the sheltered place until after the lightning or rain, so injuries or fatalities could be avoided. In addition, in a developed country like the United States, equipment like lightning rods is usually mounted on top of the buildings to effectively keep the lightning strikes from damaging the buildings. In short, although lightning strikes may directly affect GCP growth, modern society is well-equipped to prevent damages from them. Hence, I can reasonably assume the impact is marginal, and that makes the number of lightning strikes a plausible instrument for fire occurrence.

Based on my arguments above, I assume annual local precipitation and lightning strikes are exogenous to GCP growth hence plausible instruments for my models.

On the other hand, there are some measured contributions to GCP growth that could affect wildfire occurrence and magnitude. One example is the regional urbanization level, which could be measured by county population. Thus, I utilize the county-level population data to obtain a set of per-capita GCP. After adjusting for inflation, I am able to obtain the dataset of per-capita real GCP growth, which I use as the dependent variable in my models.

3.1 Regressions

Model # 1: $\Delta ln\left(GCPP_{i,t}\right) = \beta_1 \Delta ln\left(GCPP_{i,t-1}\right) + \beta_2 Fire_{i,t} + u_{i,t}$

- $\Delta ln\left(GCPP_{i,t}\right)$: change in the natural log of per capita real GCP of county i in year t
- $\Delta ln\left(GCPP_{i,t-1}\right)$: change in the natural log of per capita real GCP of county i in year t - 1
- $Fire_{i,t}$: number of fires in county i during year t
- $u_{i,t}$ = error term that is assumed heteroskedastic

Model # 2: $\Delta ln\left(GCPP_{i,t}\right) = \beta_1 \Delta ln\left(GCPP_{i,t-1}\right) + \beta_2 Dur_{i,t} + u_{i,t}$

- $\Delta ln\left(GCPP_{i,t}\right)$: change in the natural log of per capita real GCP of county i in year t
- $\Delta ln\left(GCPP_{i,t-1}\right)$: change in the natural log of per capita real GCP of county i in year t - 1
- $Dur_{i,t}$: number of fire days in county i during year t
- $u_{i,t}$ = error term that is assumed heteroskedastic

Both regressions are run with county and year fixed effects because I suspect the dependent variable $\Delta ln\left(GCPP_{i,t}\right)$, per-capita real county output growth, is affected by unobserved factors that systematically vary across counties and time in my panel. The coefficient on any variable that's correlated with this variation will have an omitted variable bias. By using fixed-effects models, I can remove omitted variable bias by measuring changes within counties and year.

Comparing to regions where technological industry predominates, natural disasters like wildfires in agriculture intense regions would likely have a greater impact on the local per capita real output growth. Policies on fire suppression or fire prevention may also vary across counties and time, and these variations are directly correlated with wildfire occurrence and intensity. Therefore, I use year and county fixed effects in my models to help address the problem caused by unobserved variations.

4 Data

4.1 County-level GDP / GCP Data

In this paper, the empirical models use GCP at constant prices (2012 US dollars) as a measure for economic activity across the US. This dataset is the first official release of GCP by the U.S. Bureau of Economic Analysis (U.S. Bureau of Economic Analysis). It covers annually reported GCP for all counties across the US from 2001 to 2018. Comparing to the state level GDP data, the GCP data helps to provide a higher spatial resolution and thus higher accuracy measurements. On the other hand, it enables county fixed effects in the models so that I can remove the omitted variable bias of the estimated coefficients caused by cross-county variation in unobserved factors.

4.2 SHELDUS Wildfire Data

I use county-level wildfire data from Arizona State University's Spatial Hazard Events and Losses Database for the United States (SHELDUS). The data contains information on time (year and month) of each fire and the real direct losses caused by the fire (property and crop losses, injuries, and fatalities) from 1960 to 2016.

For the consistency of data frequency, I convert the monthly wildfire data to annual data so that it matches the GCP data. The yearly summation is calculated for each damage variable and number of fires. For example, if there was a fire record in county A in June and another in August during year t, the annually total number of fires is 2, and the real losses caused by these fires are summed.

4.3 Data for Instruments

4.3.1 Lightning Data

For IV estimation, I utilize lightning reports by county from Lightning Products and Services of National Oceanic and Atmospheric Administration (NOAA). More specifically, I generate the annual sum of daily could-to-ground lightning flashes by county so it can be used as an instrument for fire occurrence.

4.3.2 Precipitation Data

I obtain yearly local precipitation data from North America Land Data Assimilation System (NLDAS) "Daily Precipitation years 1979-2011" on CDC WONDER online database. From the dataset, I use the annual average value of "all of the daily precipitation measurements" (NLDAS) for US counties.

4.4 Population Data

To control for population growth in my models, I use the county-level population data from "Census U.S. Intercensal County Population Data, 1970-2014" of the National Bureau of Economic Research. This dataset contains county-level population from 1970 to 2014, and it helps me to obtain the per capita GCP growth.

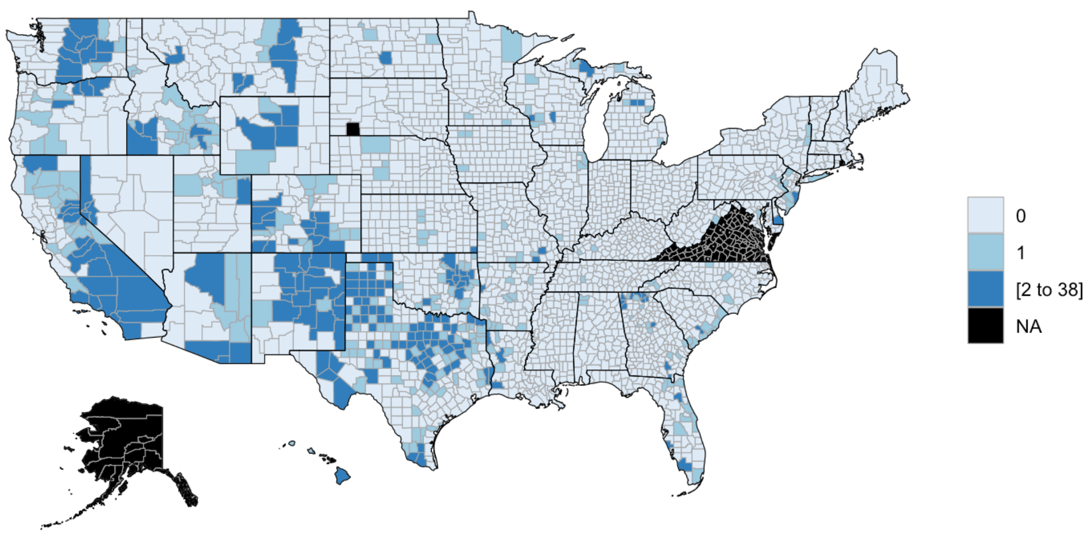
4.5 Combining Data

To combine the GCP data, the identification variables used are the county FIPS and year. FIPS stands for the five-digit U.S. Federal Information Processing Standard codes, the first two digits and the last three digits of which respectively represents the state code and county code within the state. For the initial analysis, the missing values are set to zero for losses and fire records in counties without fire record in certain years. Due to data availability limitation of other variables used in this analysis, I only use GCP data from 2001 to 2011. For the same reason, the same time period applies to data of all variables in my analysis.

Many counties have changed their borders or merged with other counties throughout 2001 to 2011, for the consistency of the analysis, they are left out from the dataset I use. Most of these counties are from Alaska. Besides, according to the wildfire data, Virginia was barely touched by wildfires during the time period; according to the GCP data, Virginia has many independent cities with small population, so the GCP data was combined for many groups of these independent cities. For these reasons, the state of Alaska and Virginia are left out from my analysis; the same applies to Shannon County, SD (renamed) and Kalawao County, Hawaii (combined with Maui County).

In the following map, I show all wildfires used in my analysis from 2001 to 2011. The eastern US experienced substantially more wildfires than western US. The areas colored as black consist of counties that are left out from my analysis. Maps of other variables (Figure Appendix.4 – 7) as well as figures showing the trend of wildfire occurrence (Figure Appendix.8 – 10) can be found in the appendix.

Figure 2: Total wildfires occurred in the US (2001 – 2011)



5 Results

First, I present the OLS estimation of my models in table 1 below.

Table 1: OLS Estimation of GCP Growth Model (with County and Year Fixed Effects)

	Dependent Variable $\Delta ln(GCPP_{i,t})$	
	(1)	(2)
$\Delta ln(GCPP_{i,t-1})$	- 0.198 *** (0.017)	- 0.198 *** (0.017)
$Fire_{i,t}$	- 3.566e-04 (2.758e-03)	
$Dur_{i,t}$		- 1.504e-04 (3.268e-04)
R^2	0.115	0.115
Adjusted R^2	0.053	0.053
Residual Std. Error	0.090	0.090
F-statistics (full model, *iid*)	1.852	1.852
F-statistics (proj model)	69.95	69.95

Note: *p < 0.1; **p < 0.05; ***p<0.01
F (proj model) refers to the F-test of all regressors (not including fixed effects), while F (full model) refers to all regressors including the fixed effects. Robust standard errors are reported. R^2 and adjusted R^2 are from the full models.

From Table 1, both fire occurrence and fire duration are statistically insignificant in the two models. Although the F-statistics of the projected models are large with the same value of 69.95, that is likely contributed by the $\Delta ln(GCPP_{i,t-1})$. Several summary statistics for the two models are identical, potentially because the effect of $\Delta ln(GCPP_{i,t-1})$ predominates in both models.

There is also potential endogeneity problem caused by omitting unobserved variables that correlate to both the dependent variables and the independent variables of interest, such as $EconType_i$ and $Supp_{i,t}$. To address the endogeneity problem, I then run the regressions again using instrumental variables. I present the results from IV estimation below in Table 2.

Table 2: TSLS Estimation of GCP Growth Model (with County and Year Fixed Effects)

	Dependent Variable $\Delta ln(GCPP_{i,t})$	
	(1)	
$\Delta ln(GCPP_{i,t-1})$	- 0.216 *** (0.021)	- 0.192 *** (0.017)
$Fire_{i,t}$	- 0.343 (0.194)	
$Dur_{i,t}$		- 0.016** (0.006)
Residual Std. Error	0.115	0.094
F-statistics (full model, *iid*)	1.137	1.723
F-statistics (proj model)	64.09	73.35
Weak IV Test	iid F = 4.418	iid F = 58.112

Note: *p < 0.1; **p < 0.05; ***p<0.01
F (proj model) refers to the F-test of all regressors (not including fixed effects), while F (full model) refers to all regressors including the fixed effects. Robust standard errors are reported.

From the two-stage least square estimation, as expected, $\Delta ln(GCPP_{i,t-1})$ is still statistically significantly contributing to $\Delta ln(GCPP_{i,t})$ in both models. Although $Fire_{i,t}$ remains statistically insignificant, the magnitude of its coefficient increases considerably, and this could be one of the results from removing the endogeneity. Fire duration, on the other hand, becomes statistically significant at 5% significance level after using annual mean precipitation as the instrument. Nevertheless, the small magnitude of the coefficient indicates practical insignificance. More specifically, the estimate suggests that 10 more days of fire duration is associated with a decrease in $\Delta ln(GCPP_{i,t})$ by only 0.16.

In Table 3 below, I present the results from the first stage of the TSLS estimation.

Table 3: First-Stage Estimation (with County and Year Fixed Effects)

	Dependent Variable	
	$Fire_{i,t}$ (model 1)	$Dur_{i,t}$ (model 2)
$\Delta ln(GCPP_{i,t-1})$	- 0.053** (0.017)	- 0.365** (0.121)
$Flash_{i,t}$	- 7.168e-07* (3.041e-07)	
$Precip_{i,t}$		- 0.144*** (0.015)
R^2	0.277	0.183
Adjusted R^2	0.227	0.126
Residual Std. Error	0.210	1.523
F-statistics (full model, *iid*)	5.492	3.213
F-statistics (proj model)	7.485	48.74
Weak IV Test	iid F = 4.418	iid F = 58.112

Note: *p < 0.1; **p < 0.05; ***p<0.01
F (proj model) refers to the F-test of all regressors (not including fixed effects), while F (full model) refers to all regressors including the fixed effects. Robust standard errors are reported.

In the first stage estimation, I regress the suspected endogenous variables, $Fire_{i,t}$ and $Dur_{i,t}$, on corresponding instruments and $\Delta ln(GCPP_{i,t-1})$ for each model respectively. From the results, lightning flash is only statistically significant at 10% level. It is also very economically insignificant: on average, 1000 more lightning flashes are associated with a decrease in yearly number of fires by only 0.0007. Through the formal weak IV test, $Flash_{i,t}$ is a weak instrument according to the rule of thumb. Besides its insignificance, the coefficient has a negative sign, which does not match with my hypothesis.

An instrument is weak when it is weakly correlated with the suspected endogenous variable. This relationship is revealed by the first stage estimation. An insignificant coefficient for the instrument variable usually indicates weak instrument problem. With a finite sample size, a weak instrument could make the IV estimators highly biased. But it might not be the major problem because my sample size is 26,883. However, with a weak instrument, it's likely I haven't removed the endogeneity from the model, so I do not have strong evidence to make a consistent conclusion based on the results of model 1.

$Precip_{i,t}$, on the other hand, has a statistically significant impact on fire duration days at 1% level. $Precip_{i,t}$ is not a weak instrument according to the weak IV test, but it is practically insignificant. With every millimeter increase in yearly average of daily precipitation, the fire duration is expected to decrease by 0.144 days. The maximum of $Precip_{i,t}$ in my dataset is about 9 millimeters, and 9 more millimeters in $Precip_{i,t}$ would only decrease fire duration by about 1.3 days.

6 Conclusion and Discussion

In this paper, using IV estimation with fixed effects, I do not find statistically significant evidence for the impact that fire occurrence has on per capita real GCP growth. It is likely because the number of lightning flash is a weak instrument. On the other hand, at 5% significance level, I find statistically significant evidence for the negative impact that fire duration has on real GCPP growth, but the effect is economically very insignificant. With 10 more days of fire duration, GCPP growth rate decreases by only 0.16.

The results of my models show that wildfires have little effect on GCPP growth, but one limitation of my analysis is that only GCP data for "all industry total" is used to estimate the total economic activity for each county. If GCP data for each industry was used, the results may appear differently because for example, wildfires likely have a greater impact on agriculture, forestry, fishing and hunting than on arts, entertainment, and recreation.

Moreover, precipitation could potentially affect other natural disasters like floods, which cause damage to communities across the US and thus adversely impact economic activity. Hence, there is a chance that precipitation is not a valid instrument for my model. Future analysis that utilizes industry specific GCP data and better instruments is needed.

Reference

Borgschulte, M., Molitor, and D., Zou, E.Y. (2019). Air Pollution and the Labor Market:Evidence from Wildfire Smoke. Retrieved April 23, 2020 from https://static1.squarespace.com/static/56034c20e4b047f1e0c1bfca/t/5dcde5d5ed33d22b3aa21e09/1573774811503/Smoke_and_Labor.pdf

Butry,D.T., Mercer, E.D., Prestemon, J.P., Pye, J.M, and Holmes, T.P. (2001). What Is the Price of Catastrophic Wildfire? Journal of Forestry, 99(11), 9–17. https://doi.org/10.1093/jof/99.11.9

CALIFORNIA Health Care Almanac (CHCF). (2019). Health Care Costs 101: Spending Keeps Growing. Retrieved April 23, 2020 from https://www.chcf.org/wp-content/uploads/2019/05/HealthCareCostsAlmanac2019.pdf

Hesseln, H., Loomis, J. B., González-Cabán, A., and Alexander, S. (2003). Wildfire effects on hiking and biking demand in new mexico: A travel cost study. Journal of Environmental Management, 69(4), 359-368. doi:10.1016/j.jenvman.2003.09.012

Hope E.S., McKenney D.W., Pedlar J.H., Stocks B.J., and Gauthier S. (2016). Wildfire Suppression Costs for Canada under a Changing Climate. PLoS ONE 11(8): e0157425. doi:10.1371/journal.pone.0157425

Miller, N., Molitor, D., and Zou, E. (2017). Blowing Smoke: Health Impacts of Wildfire Plume Dynamics. Retrieved April 23, 2020 from https://static1.squarespace.com/static/56034c20e4b047f1e0c1bfca/t/59e2e4fe0100271556d54e1a/1508041986866/smoke_MMZ_201710.pdf

Moeltner, K., Kim, M. -., Zhu, E., and Yang, W. (2013). Wildfire smoke and health impacts: A closer look at fire attributes and their marginal effects. Journal of Environmental Economics and Management, 66(3), 476-496. doi:10.1016/j.jeem.2013.09.004

Molina, J. R., González-Cabán, A., and Rodríguez y Silva, F. (2019). Wildfires impact on the economic susceptibility of recreation activities: Application in a Mediterranean protected area. *Journal of Environmental Management, 245*, 454-463. https://doi.org/10.1016/j.jenvman.2019.05.131

Mosely, C., Gebert, K., Jakes, P., Leete, L., Nielsen-Pincus, M., Davis, E. J., Evers, C., Rishel, B., Sundstrom, S., Ellison, A., Conaghan, K., Katra, A., Podowski, L., and Rinaldi, N.(2012). The Economic Effects of Large Fires. *Ecosystem Workforce Program.* Retrieved April 2, 2020 from https://www.firescience.gov/projects/09-1-10-3/project/09-1-10-3_final_report.pdf

National Interagency Fire Center (NIFC). (n.d.). “Suppression Costs (1985-2018)”. *Statistics-Historical Wildland Fire Information.* Retrieved April 2, 2020 from https://www.nifc.gov/fireInfo/fireInfo_statistics.html

National Interagency Fire Center (NIFC). (n.d.). “Total Wildland Fires and Acres (1926-2019)”. Retrieved April 2, 2020 from https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html

North America Land Data Assimilation System (NLDAS) Daily Air Temperatures and Heat Index, years 1979-2011 on CDC WONDER Online Database. (2013). Retrieved April 2, 2020 from http://wonder.cdc.gov/NASA-NLDAS.html

North America Land Data Assimilation System (NLDAS) Daily Precipitation years 1979-2011 on CDC WONDER Online Database. (2012). Retrieved April 2, 2020 from https://wonder.cdc.gov/controller/datarequest/D81;jsessionid=C5EE8EA7C14D171AB5E9856427BBAD73

Sean C. P. C., François-Nicolas R., Piyush J., Mike D. F. (2019). Scientists’ warning on wildfire — a Canadian perspective. *Canadian Journal of Forest Research, 49*(9), 1015-1023. https://doi.org/10.1139/cjfr-2019-0094

Soaga, J. A., Shotuyo, A. L. A., and Fatoki, J. G. (2013). Socio-economic impact of seasonal wildfire on forest and wildlife biodiversity in Ogun state. International Journal of Molecular Evolution and Biodiversity, 3(2) doi:10.5376/ijmeb.2013.03.0002

Stetler, K.M., Venn, T.J., and Calkin, D.E. (2010). The effects of wildfire and environmental amenities on property values in northwest Montana, USA. Ecological Economics. 69(11), 2233-2243. https://doi.org/10.1016/j.ecolecon.2010.06.009

The National Bureau of Economic Research. (2016). Census U.S. Intercensal County Population Data, 1970-2014. Retrieved April 2, 2020 from http://data.nber.org/data/census-intercensal-county-population.html

United States Forest Service (USFS). (2013). "Wildfire, Wildlands, and People: Understanding and Preparing for Wildfire in the Wildland-Urban Interface." Retrieved April 23, 2020 from http://www.fs.fed.us/openspace/fote/reports/GTR-299.pdf

United States Forest Service (USFS). (2013). "Wildfire, Wildlands, and People: Understanding and Preparing for Wildfire in the Wildland-Urban Interface." Retrieved April 23, 2020 from http://www.fs.fed.us/openspace/fote/reports/GTR-299.pdf

U.S. Bureau of Economic Analysis. (2019). Local Area Gross Domestic Product, 2018. Retrieved from https://www.bea.gov/news/2019/local-area-gross-domestic-product-2018

U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average [CPIAUCSL]. (2020). Retrieved April 23, 2020 from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL

Wood, D. (2015). An Economic Approach to Measuring the Impacts of Higher Temperatures on Wildfire Size in the Western United States. 2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California 205979, Agricultural and Applied Economics Association. Retrieved April 23, 2020 https://ageconsearch.umn.edu/record/205979/?ln=en

Appendix

1. Summaries of General Wildfire Statistics in the US

Figure Appendix.1: Average Size of Wildfires in the US (1985 – 2018)

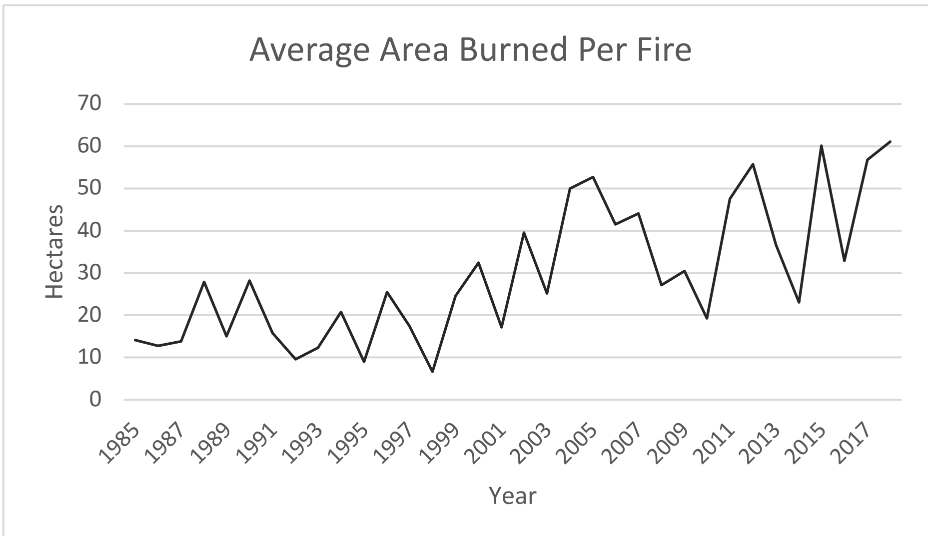


Figure Appendix.2: Number of Wildfires in the US (1985 – 2018)

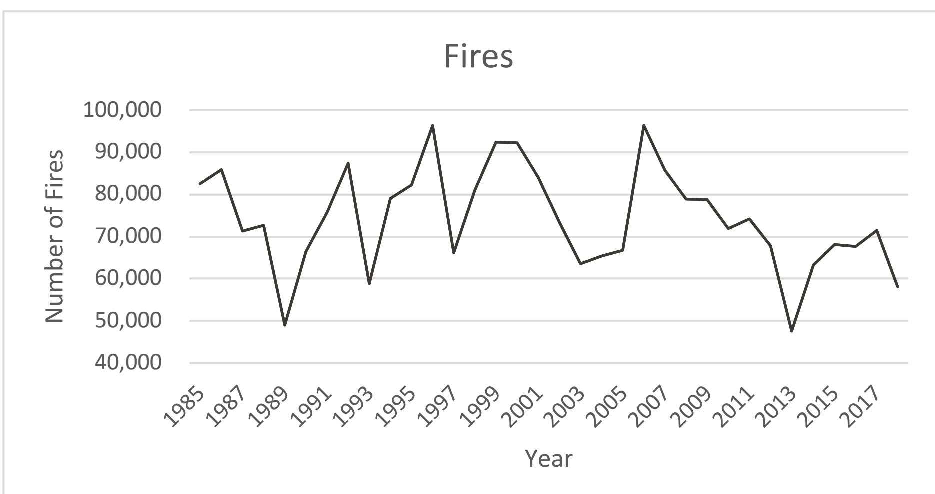
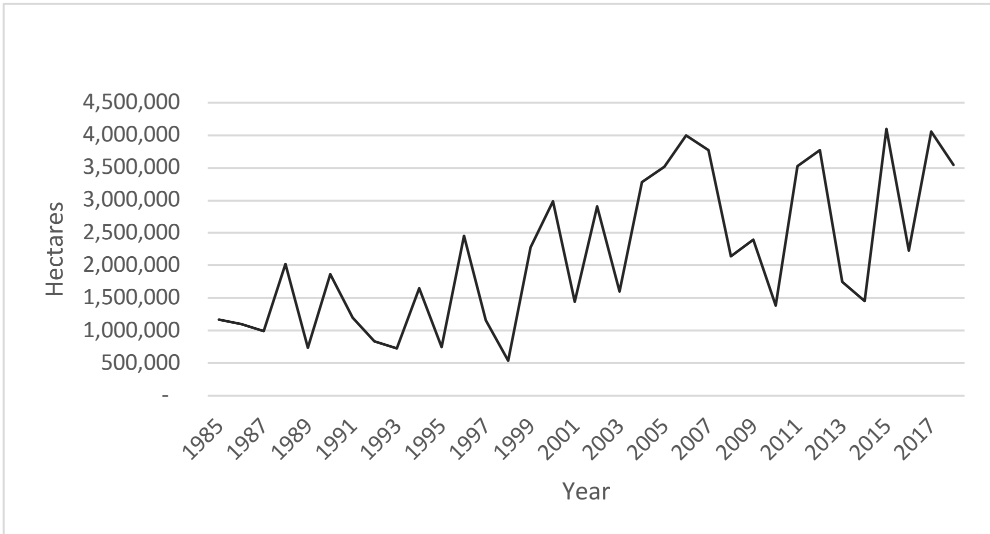


Figure Appendix.3: Area (Hectares) Burned by Wildfires in the US (1985 – 2018)



2. Maps showing the variable means (2001 – 2011)

Figure Appendix.4: Mean GCP (2012 US Dollars) in the US (2001 – 2011)

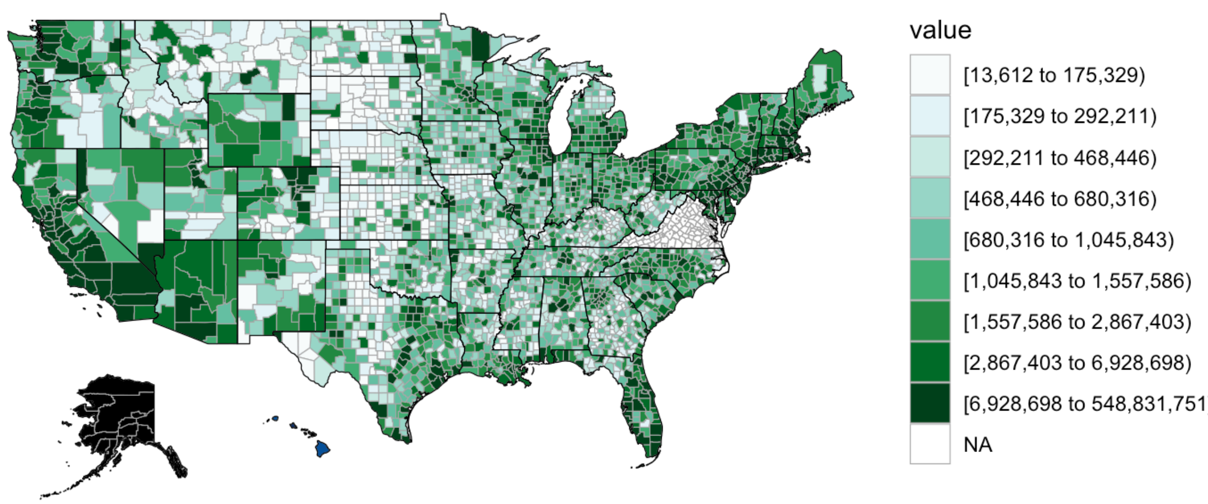


Figure Appendix.5: Mean Number of Lightning Flashes in the US (2001 – 2011)

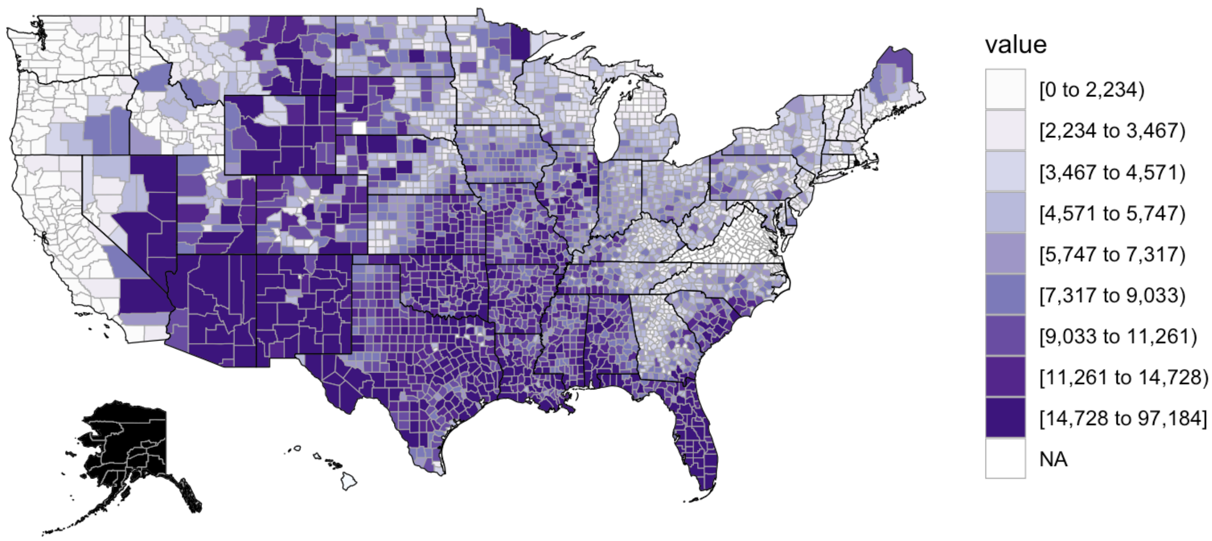


Figure Appendix.6: Mean Precipitation (Millimetres) in the US (2001 – 2011)

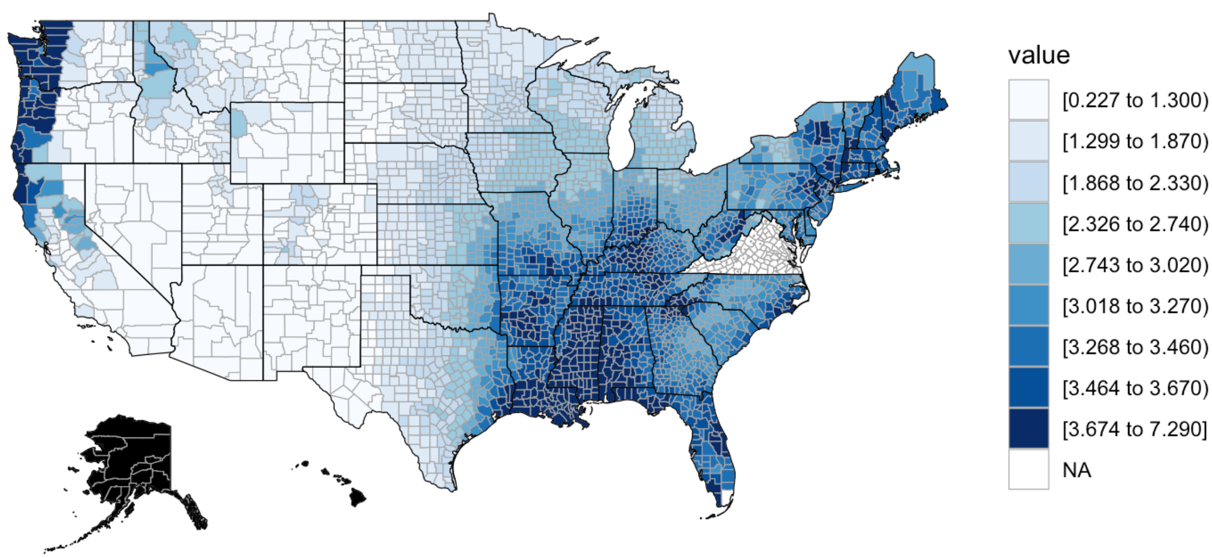
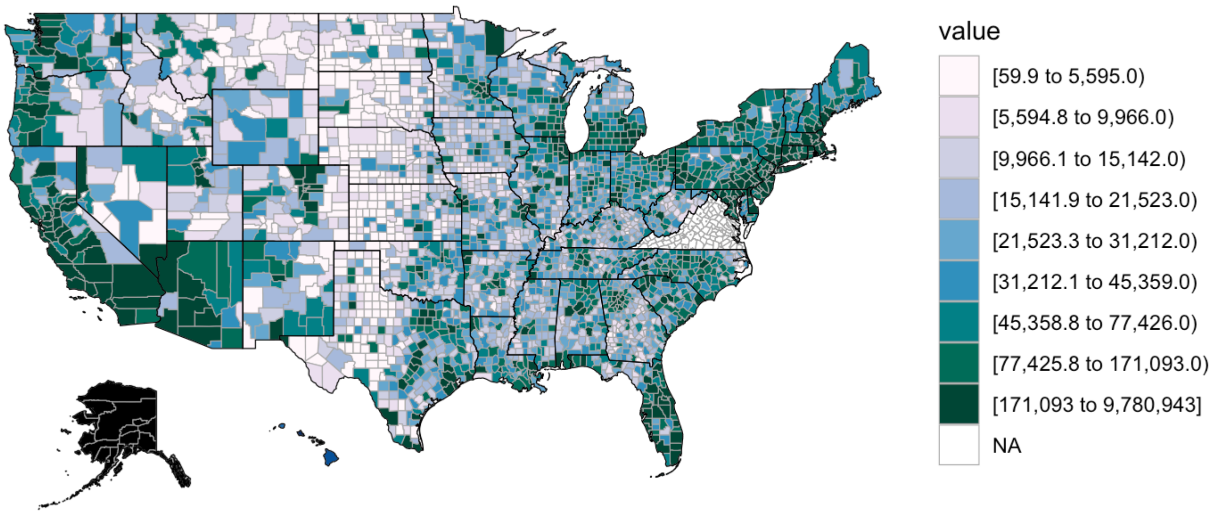


Figure Appendix.7: Mean Population in the US (2001 – 2011)



3. Maps showing the numbers of fires across time and counties.

Figure Appendix.8: Wildfires Occurred in the US in 2003

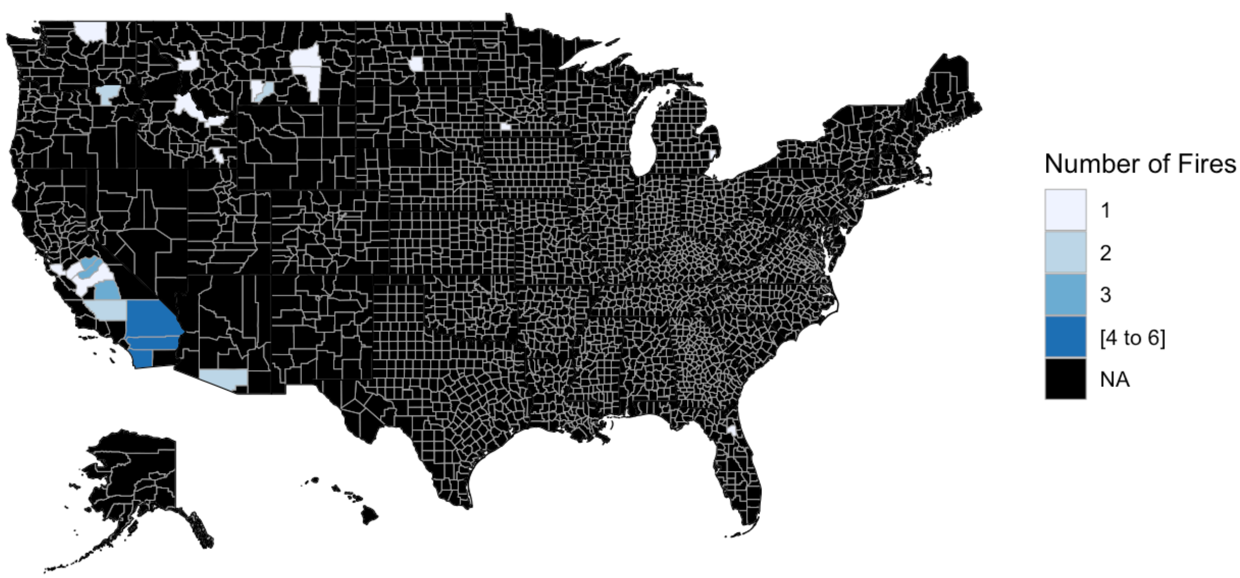


Figure Appendix.9: Wildfires Occurred in the US in 2007

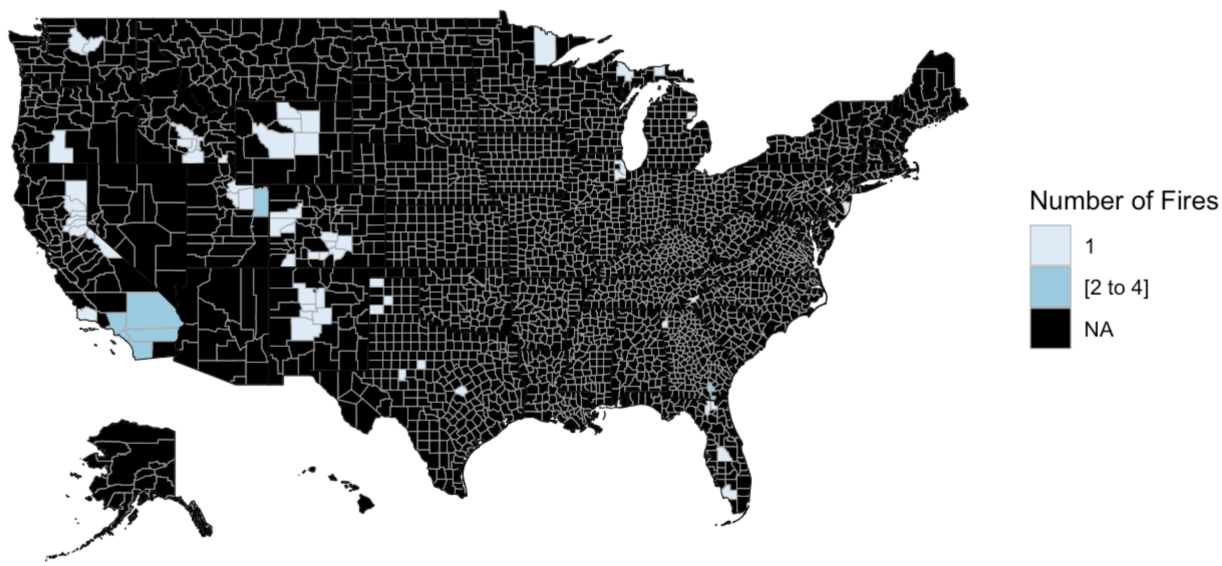


Figure Appendix.10: Wildfires Occurred in the US in 2011