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Residential Housing Labor Market Outcomes following Wildfires: A Case Study of the 2018 Camp Fire

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Wildfires in recent years have posed a great threat to residential properties and local economies in communities located near the wildland-urban interface (WUI), particularly in the state of California. Wildfires destroy residential properties, disrupting the residential construction supply chains. When the residential housing stock is destroyed by wildfires, rebuilding must quickly begin to avoid disrupting the local community and economy. This process intensifies the demand for residential construction material resources and requires the local construction labor market to sustain the demand for construction labor over time and manage the influx of workers. Using an interrupted time series analysis, this study investigates the dynamic impacts of wildfires on the residential construction sector, utilizing residential permits and labor employment data from a case study of the 2018 Camp Fire in Butte County, California. Results indicate that the wildfire promoted a sustained increase in residential construction activity (average post-fire permit valuations increased by 67%), matched by a consistent rise in labor employment (average post-fire labor concentration increased by 25%). The findings provide insights into the resilience of residential construction sectors in the face of wildfires.

Key Words: Wildfires, Labor market, Residential construction, Time series analysis

Introduction

U.S. wildfires have been growing in frequency and intensity in recent years due to climate change (Abatzoglou & Williams, 2016). Over the past few decades, wildfires have become more widespread, particularly in the western U.S. For example, wildfires burned an annual average of 3.3 million acres in the 1990s compared to over 7.0 million acres annually since 2000 (Congressional Research Service, 2023). Wildfires have also become more destructive (e.g., number of structures burned, associated financial damages, and costs required for reconstruction) due to the rapid expansion of the wildland-urban interface (WUI) — defined as the zone of transition between unoccupied land and human development (Radeloff et al., 2018). The state of California exemplifies this growing risk of wildfires across western states. A recent study by Buechi et al. (2021) found that the average annual

area burned due to wildfires in California rose from 337,000 acres over the 1979-1988 decade to 708,000 acres during the 2009-2018 decade. Additionally, the area burned within WUI zones grew from an average of 22,000 acres per year to over 32,000 acres annually during those same decades. As the number of structures damaged by wildfires grows, so too do the costs to rebuild and restore community functionality. Monetary losses from wildfires have risen exponentially, from an annual average loss of \$30 million in the 1979-1988 decade to almost \$1 billion in the 2009-2018 decade (Buechi et al., 2021). These trends highlight the growing vulnerability of residential properties due to wildfires, as illustrated by the recent 2018 Camp Fire – one of the most destructive wildfires in California history. The focus of this study is on the 2018 Camp Fire.

The Camp Fire ignited on November 8, 2018, close to Pulga in Butte County, Northern California, due to a live powerline from Pacific Gas and Electric (PG&E) being disrupted (NOAA, 2020). The fire engulfed the town of Paradise in Butte County, California, destroying over 18,000 structures and causing over \$16 billion in damages (Cal Fire, 2023). Within hours, the flames devastated Paradise and other nearby communities. The fire was fully under control by November 25, 2018. Approximately 95% of the structures in both Paradise and Concow were destroyed, leaving both towns in ashes. The fire damaged 754 structures and completely destroyed a total of 18,800 structures which were mostly single-family residential homes (Cal Fire, 2023).

Swift rebuilding of the residential housing stock after wildfires is crucial for recovery and long-term community resilience. However, rebuilding damaged or destroyed residential houses following wildfires presents a formidable challenge, intensified by the element of time compression commonly observed after major disasters (Olshansky et al., 2012). After a wildfire event, communities face an urgency to restore community functionality and the residential housing stock as quickly as possible, condensing the post-disaster reconstruction timeframe process. This urgency demands a rapid mobilization of reconstruction resources, such as construction labor and materials, often at a pace that leads to disparities in the rebuilding process. Pre-disaster shortages of skilled labor (Chang-Richards et al., 2017) are exacerbated by time compression in the context of post-disaster reconstruction, resulting in demand surge (i.e., sudden increases in the price of labor) (Olsen & Porter, 2011), making rebuilding a challenging process. This has implications for the local labor market, especially if the affected area previously did not have a surplus of construction labor (Mockrin et al., 2015). Thus, a comprehensive understanding of how wildfire events influence both physical rebuilding patterns and associated labor market shifts can help guide future policy and planning to make the residential construction market resilient to such events in wildfire-prone areas.

Literature Review

Disasters disrupt the normal functioning of the residential construction industry as homeowners drive up post-disaster demand for construction services to meet rebuilding requirements, often constraining the capacity of the regional market to supply labor and material resources (Pradhan & Arneson, 2021). This is evident in the aftermath of wildfires when homeowners decide to rebuild. For instance, a study of post-fire rebuilding patterns following wildfires in the conterminous U.S. from 2000 to 2005 showed that while only 25% of burned homes were rebuilt within five years, the overall number of buildings within the fire perimeter actually increased post-fire, indicating a complex interplay of homeowner decisions, economic factors, and risk-assessment in wildfire-affected areas (Alexandre et al., 2015). Kramer et al. (2021) investigated post-fire rebuilding patterns following 28 of the most destructive wildfires in California spanning 1970-2009 and found sustained demand for construction services post-wildfire with 58% of destroyed buildings being rebuilt within three to six years and 94% within thirteen to twenty-five years after the fire.

While building materials can be quickly sourced from different parts of the world to cater to increased construction demand in wildfire-affected regions, the same cannot be said for labor since labor markets tend to be strongly regional (Döhrmann et al., 2013). Labor mobility is a key factor in these dynamics, as workers may leave disaster-affected areas, impacting local businesses and wages, and may return after normalcy (Belasen & Polachek, 2009). The impact of wildfires on local labor markets has been shown to vary by industry sector and region, creating positive shocks (e.g., growth in employment due to the creation of new job opportunities in sectors like disaster recovery and rebuilding) or negative shocks (e.g., decline in employment by disruption of existing industries and displacement of workers). For example, Nielsen-Pincus et al. (2012) conducted a study examining the effects of large wildfires on local labor markets in the Western U.S. from 2004 to 2008. They found that during quarters with active wildfires, employment and wages in wildfire-affected counties increased beyond statewide averages, indicating short-term positive economic impacts of large wildfires on local economies. In a case study of the 2008 Trinity County wildfires in California, Davis et al. (2014) found a decline in private-sector employment and wages but an increase in public-sector employment and wages. Jones & McDermott (2021) investigated the economic consequences of large wildfires on U.S. labor markets in wildfire-affected communities from 2010 to 2017 and found that counties within large fire zones faced significantly reduced per capita wage earnings for up to two years post-event. Luo (2023) investigated the impact of destructive wildfires in California on short-term employment from 2003 to 2021, highlighting that while overall employment suffered a minor, short-term decline, specific sectors like construction and professional services experienced growth up to 18 months post-fire. Additionally, Borgschulte et al. (2016) studied the influence of wildfire smoke air pollution on labor markets and revealed that U.S. workers experienced an average earnings loss of 9% per day of smoke exposure, leading to national economic losses of over \$30 billion annually, thereby influencing labor demand and potentially driving decisions to retire or exit the labor market.

While much of the existing literature has discussed varied impacts of wildfires on various job sectors in affected regions, there are limited studies on the dynamic impacts on the residential construction sector, especially following a single most destructive wildfire event. This study addresses the gap, focusing on the aftermath of the November 2018 Camp Fire in Butte County, California as it was the most destructive fire in the history of California. Leveraging an interrupted time series analysis, the authors address two research questions: (i) *How did the 2018 Camp Fire influence the demand for residential construction in Butte County, California?* and (ii) *What were the consequent impacts on the residential construction labor employment following the wildfire?*

Methods

A multi-step process was conducted which included (1) Selection of the case study region, (2) Data collection, and (3) Development of time series intervention models. Data analysis was conducted in Python programming language. The authors used the 2018 Camp Fire as a case study wildfire incident since it was the most destructive wildfire in California's history. Data collection included the collection of residential building permits and residential labor employment time series data. The authors used residential building permit frequency and permit values (\$USD) to highlight residential reconstruction activities following the wildfire. Monthly residential building permit frequency and valuation data was collected for the years 2014 to 2022 from the Monthly Building Permit Activity Reports dataset publicly available from the Butte County Official Website (Development Services, Butte County Official Website, 2023), which included 4 years of pre-fire and 4 years of post-fire data points. Only the permits under residential construction were analyzed, which included the number and valuation of residential projects permitted each month. The authors manually extracted the permit data from the dataset which was originally in portable document (PDF) format. The concentration of the

residential construction labor market was accessed using a location quotient (LQ) of the monthly labor employment for the residential construction sector. LQ is a statistical measure that determines the concentration of a particular industry in a specific region compared to a larger reference area, typically a nation (i.e., the U.S.). LQ was used as it facilitates the comparison of regional employment with the national average (Pradhan et al., 2023). The authors used employment data from the North American Industry Classification System (NAICS) sector 2361 as it comprised establishments primarily responsible for the construction of new residential buildings. Monthly employment LQ data for Butte County was obtained from the years 2014 to 2022 from the Quarterly Census of Employment and Wages (QCEW) data published by the U.S. Bureau of Labor Statistics (2023).

Since the goal of this study was to analyze how the 2018 Camp Fire influenced shifts in the residential construction sector over time, an Interrupted Time Series (ITS) analysis was utilized. ITS is particularly useful in assessing the impact of an intervention (e.g., in this case, the wildfire) on a continuous sequence of data (e.g., in this case, permits and employment), thereby illuminating trends and shifts in a specific sector over time. Given the nature of the data collected, which comprised a time series, the authors employed a specialized variant of the ITS, called the Auto-Regressive Integrated Moving Average (ARIMA) based ITS model. This choice was driven by the ARIMA model's ability to handle time series data characterized by recurring patterns (i.e., seasonality) and the interconnectedness of sequential data points (i.e., autocorrelation) (Schaffer et al., 2021).

ARIMA is a prominent forecasting method for univariate time series data. It melds three key components: autoregression (AR), which uses past values as predictors; differencing (I), which aims to make the series stationary by removing trends and seasonality through subtraction of consecutive observations; and moving average (MA), which accounts for correlations between observations and residual errors from previous time points. In specifying an ARIMA model, three parameters are identified, also referred to as the order of the ARIMA model: the number of lagged observations (p), the degree of differencing (d), and the size of the moving average window (q). The general equation of the $ARIMA(p, d, q)$ model is given in equation 1 (Hyndman & Athanasopoulos, 2018).

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \dots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad 1$$

where y'_t is the time series after differencing d times; c is constant; ϕ_i are coefficients for the autoregressive terms; θ_i are coefficients for moving average terms; and ε_t is the error term. This equation forecasts future values by analyzing both historical patterns and prediction errors.

In the ARIMA model, the parameters p , d , and q are chosen first to best fit the pre-intervention time series. The value d indicates the number of differences required to make the time series stationary (i.e., constant mean and variance), often identified through tests like the Augmented Dickey-Fuller test (Dickey & Fuller, 1981). The Partial Autocorrelation Function (PACF) plot, which shows the series' correlation with its lags after adjusting for previous correlations, helps determine the number of AR (autoregressive) terms p . The Autocorrelation Function (ACF) plot, which displays the series' correlation with its own lags, helps identify the number of moving average (MA) terms q . An alternative to these classical methods of model selection is the use of the Akaike Information Criterion (AIC) to systematically compare and select the most suitable $ARIMA(p, d, q)$ model by evaluating various model orders and choosing the one that minimizes the information loss while penalizing for increasing complexity. Once the potential ARIMA order was identified, the ARIMA model was re-estimated for the entire time series by introducing an intervention variable I_t as shown in equation 2.

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \dots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t + \delta I_t \quad 2$$

where δ is the magnitude of the intervention effect and I_t is a categorical variable which typically takes the value 0 before the intervention and 1 during or after the intervention. In order to analyze short-term and long-term effects, the term I_t was assigned two functional forms: pulse function and step function (Schaffer et al., 2021). A pulse function represents a single, abrupt change in a time series at a specific point in time, while a step function denotes a permanent shift in the level of a time series starting from a particular intervention point onward. If T is the time of intervention (i.e., the ignition month of wildfire), then the intervention term I_t takes the following values:

- i) Pulse function: $I_t = 0$ for $t \neq T$ and $I_t = 1$ for $t = T$
- ii) Step function: $I_t = 0$ for $t \neq T$ and $I_t = 1$ for $t > T$

Results and Discussion

An ARIMA Interrupted Time Series model was constructed using the residential building permits and labor employment time series data for Butte County, California to study the dynamic impacts of the 2018 Camp Fire on the residential construction permits and labor employment.

Residential Construction Permits

Figure 1 shows the bar plot of pre-wildfire residential permits and post-wildfire reconstruction permits issued by Butte County, CA. The vertical dotted line shows the 2018 Camp Fire incidence month (November 2018). The mean monthly permit count in the four years before the Camp Fire was 14 while the mean monthly permit count in the four years after the wildfire was 26. Out of all the post-fire permits in Butte County, CA, 41% were directly related to Camp Fire rebuilding projects according to the permit data. Figure 1 highlights that the rebuilding process started four months following the wildfire. The number of rebuilding permits was relatively higher in the first two years following the wildfire (i.e., 2019-2020) and slowly declined in the subsequent years.

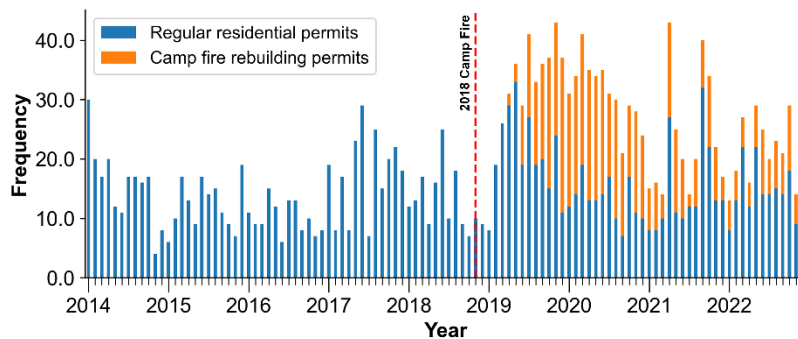


Figure 1. Frequency of residential permits in Butte County, CA

The monthly time series of the residential building permit valuation is shown in Figure 2. From the plot, it was observed that the monthly valuation (\$USD) of building permits issued by Butte County, CA increased following the wildfire. The mean monthly residential permit valuation before the fire was around \$3 million USD while the mean monthly valuation post-fire was over \$5 million USD. In other words, it added more construction workload in Butte County compared to pre-fire. The four-year pre-wildfire intervention period was compared against the four-year following the 2018 Camp Fire. The ARIMA model was first fitted to the pre-intervention data. The Augmented Dickey-Fuller

(ADF) test for stationarity of time series found that the pre-intervention time series was non-stationary with a test statistic of -2.73 and a p-value of 0.06. The optimum value of $ARIMA(p, d, q)$ was computed using the grid search method which involved automatically testing a range of values for the autoregressive (p), differencing (d), and moving average (q) parameters. The best combination was selected based on the Akaike Information Criterion (AIC), which helped determine the goodness of fit of the model while penalizing for model complexity. This yielded $ARIMA(2,1,3)$ model for the valuation of building permits. In Figure 2, the predicted series inside the 95% confidence interval (CI) band shows the counterfactual forecast using the ARIMA model following the fire. In other words, it showed what the predicted values would have been post-intervention mark if the wildfire event had not occurred. Clearly, the wildfire had a significant impact on the valuation of building permits issued in the long run as shown by the actual permit value trending higher than counterfactual prediction.

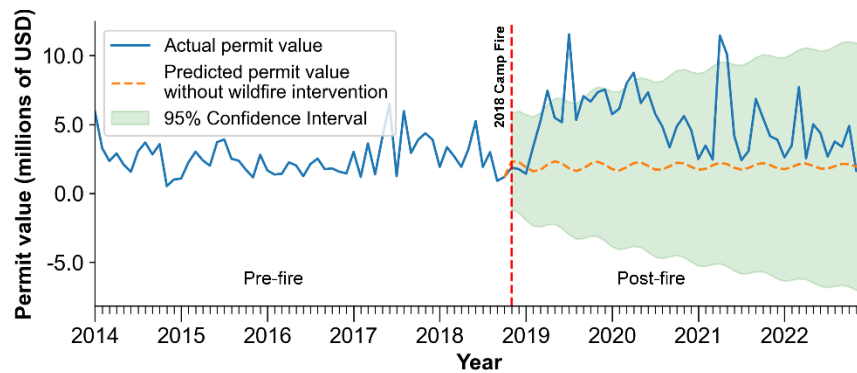


Figure 2. Time series of residential permit value with counterfactual forecast in Butte County, CA

The results of the ARIMA-ITS model in Table 1 show that for the short-term effect, the intervention coefficient was negative and statistically insignificant while for the permanent effect, the coefficient was positive and statistically significant. This suggested that while the wildfire intervention might not have shown immediate changes to permit activity, it brought growth in the long run by adding a sustained amount of residential construction work by approximately \$2.26 million.

Table 1

Results of the ARIMA-ITS model for residential permits

Time series	ARIMA Model	Intervention function	Duration of intervention	Intervention Coefficient	p-value
PERMIT	(2,1,3)	Pulse	Wildfire month	-1.6182	0.456
PERMIT	(2,1,3)	Step	Post-wildfire months	2.2636	0.004*

Residential Labor Employment

Figure 3 shows the monthly time series of location quotient (LQ) of the monthly employment of construction labor employed in the residential construction sector (NAICS 2361) in Butte County, CA. When $LQ = 1$, the region and the reference area (i.e., the U.S.) have the same concentration of that industry or occupation. $LQ > 1$ indicates a higher concentration than the national average, suggesting a regional specialization while $LQ < 1$ shows that the industry is less concentrated in the region than the national average. The mean monthly employment LQ before the fire was 1.35 while

the mean monthly LQ after the fire was 1.69. Notably, a few months after this fire event, there was a clear uptick in the location quotient, suggesting shifts in the regional employment landscape post-fire.

The ARIMA model was first fitted to the pre-intervention series. The ADF test for stationarity of time series found that the time series was non-stationary with a test statistic of -2.09 and a p-value of 0.24. The best fitting model was found to be *ARIMA(0,1,0)*. Figure 3 shows the counterfactual forecast made by the ARIMA model without the wildfire intervention which was predicted for post-fire duration. The actual employment trend extends above the 95% CI band showing significant deviation from the actual trend. The predicted line seems straight as the *ARIMA(0,1,0)* model, commonly referred to as a ‘random walk’ (Hyndman & Athanasopoulos, 2018), assumes that future values will continue to change at the same average rate as the past, without accounting for wildfire.

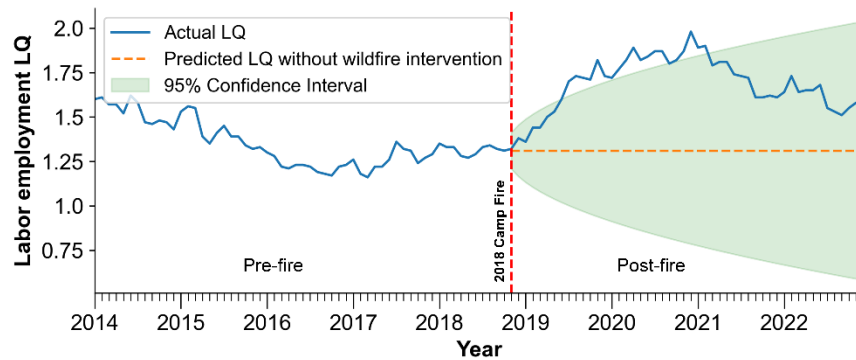


Figure 3. Time series of LQ of residential construction labor (NAICS 2361) in Butte County, CA

Table 2 shows the results of the ARIMA-ITS model for the employment time series. For the short-term effect denoted by the pulse function, the coefficient was negative but was not statistically significant. The negative coefficient denotes the decrease in LQ of employment. For the permanent effect denoted by the step function, the coefficient was positive and statistically significant. This meant that the long-term impact on the employment level was positive, indicating a sustained increase in the LQ of employment by +0.06 after the wildfire event. In contrast, the short-term dip represented by the negative coefficient (p-value >0.05) suggests that while there might have been an initial decline in employment after the intervention, it did not have a prolonged and significant effect.

Table 2

Results of the ARIMA-ITS model for residential labor employment

Time series	ARIMA Model	Intervention function	Duration of intervention	Intervention Coefficient	p-value
EMPLOYMENT	(0,1,0)	Pulse	Wildfire month	-0.0250	0.653
EMPLOYMENT	(0,1,0)	Step	Post-wildfire months	0.06	0.000*

Conclusion

This study quantified the short and long-term effects of the 2018 Camp Fire on the residential construction sector using an interrupted time series analysis of the monthly residential building permits valuation and residential labor employment location quotient (LQ) in Butte County,

California. In addressing the first research question on the impact of the wildfire on the residential construction demand, the findings revealed that there was a statistically significant sustained increase in the amount of residential construction work added after the wildfire (i.e., long-term growth) compared to what would have been expected if the wildfire had not occurred. In addressing the second research question on the impact of wildfire on residential labor employment, the findings showed that there was a statistically significant sustained increase in labor employment concentration after the wildfire. The results align with the observations of the recent BLS report showing that past major California fires saw a rapid rebound in the labor market (U.S. Bureau of Labor Statistics, 2020).

From this case study, several key lessons were learned contributing to our understanding of wildfire recovery planning and workforce development. The 2018 Camp Fire was one of the most destructive wildfires in the history of California, destroying over 18,000 structures. Rebuilding after such destructive wildfires is a time and resource consuming process. The extensive destruction of residential buildings created a long-term demand for construction services and labor in the wildfire-affected region as shown by this case study. The findings underscore the importance of adaptive planning in wildfire-prone areas, not only by strengthening building codes and construction practices to mitigate future wildfire risk but also by ensuring the labor force is adequately equipped with the necessary skills and resources for post-fire rebuilding. Furthermore, the study highlights the critical role of effective coordination among local government, city planners, policymakers, construction firms, and labor organizations in responding to sudden changes in labor market demands following destructive wildfires. These insights point towards the need for a proactive approach in workforce training and development, particularly in areas susceptible to wildfires such as California.

The study has some limitations. While the interrupted time series model highlighted the impact of the 2018 Camp Fire on Butte County's residential construction workload and labor market trends, it inherently focused on the wildfire as the primary influencing event, potentially overlooking the concurrent effects of other factors such as broader economic trends and shifts in housing policies, which could also affect the residential construction sector. Future research can incorporate these additional factors in the analysis using time series models such as Vector Autoregression (VAR).

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