The Effects of Extreme Wildfire and Smoke Events on Household Financial Outcomes *

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ABSTRACT

We evaluate the impact of extreme US wildfires and related smoke and air pollution events on household mobility, housing and financial outcomes. The analysis relies on information on the fire burn footprint and related structure damage from the US National Incident Command System, high-resolution smoke plume information from remote satellite sensing data, and measurements of changes in air quality from ground-level pollution monitors. We focus on extreme wildfires over the 2016-2020 period and use the variation in fire, smoke and pollution incidence within and beyond treatment areas to assess event outcomes. Our findings show significantly heightened credit distress among households that experienced the most destructive wildfires. Further, extreme wildfire events resulted in sizable house price declines and net out-migration from fire zones. More distant wildfire-related smoke and air pollution resulted in higher levels of credit card and mortgage defaults. The paper provides new estimates of broad adverse household financial effects associated both with direct wildfire and related indirect smoke and pollution events.

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I. Introduction

Over the past decade, wildfire activity has become both more extreme and more destructive. In the years 2015, 2017, and 2020, an annual total of 10 million acres burned, roughly equivalent to the combined area of the 75 largest cities in the United States.[1] Despite the growing impact of extreme wildfire events, there is limited evidence of their effects on household economic and financial well-being. Recent years have seen some progress in addressing these issues, (see, for example, Sharygin (2021), Winkler and Rouleau (2021)), (Issler et al. (2020), and McConnell et al. (2021)). Our paper brings new and highly articulated data to assessment of both direct fire and indirect smoke and pollution effects of extreme wildfire events on household mobility, house price, and financial outcomes.

Adverse effects of extreme wildfires extend beyond the perimeter of the fire owing to the broad diffusion of fire-related smoke and particulate pollution. These air quality effects are typically not accounted for in assessments of wildfire economic effects. Wildfire smoke events are commonplace: In 2020, U.S. counties were fully covered by wildfire smoke for an average of 20.2 days per year, and in California for an average of 64 days per year.[2] Wildfire smoke has been linked to degradation in air quality: Johnston et al. (2012) and Borgschulte et al. (2022) document that wildfire smoke plumes create sharp air pollution shocks: at the daily level, an additional day of wildfire smoke increases concentrations of ground-level fine particulate matter (PM2.5) by an average of 2.2 g/m3, or about one-third of the daily standard deviation in air quality. As broadly appreciated, air pollution may have negative effects on both health (Deryugina et al., 2019),[3] and non-health outcomes (see Aguilar-Gomez et al. (2022) for a review). Long-run longitudinal studies, for example, have shown that exposure to adverse economic and environmental conditions in early childhood can result in lower levels of educational attainment and earnings later in life (Isen et al., 2017).

This paper examines the effect of wildfire and wildfire-related smoke and pollution events on household economic and financial outcomes. The analysis is based on exhaustive and geographically-precise informative from the US National Incident Command System Incident Status Summary Forms on all wildfires causing at least some structural

[1] According to the National Oceanic and Atmospheric Administration, between 1980 and 2020 the United States had 18 wildfire events that caused more than $1 billion in damage; 15 of those have occurred since 2000. Over the past few decades, the United States has routinely spent more than $1 billion per year to fight wildfires.

[2] Wildfire smoke, like other forms of air pollution, contains particulate matter that enters the lungs and can pass into the bloodstream. Smoke also carries other pollutants, such as ozone, carbon monoxide, and a range of VOCs.

[3] Reid et al. (2016), Cascio (2018), and Xu et al. (2020) showed that increase in air pollution can lead to significant adverse health outcomes. Other studies of the health effects of wildfire smoke have linked exposure to increases in adult mortality (Miller et al., 2021), increases in infant mortality (Jayachandran, 2009), elevated risk of low birth weight (McCoy and Walsh, 2018), and reductions in lung capacity (Pakhtigian, 2022).

damage (St Denis et al. (2020)).[4] We use high-resolution remote sensing data from satellites to show the locations and temporal incidence of related wildfire smoke plumes Miller et al. (2021). We estimate the effects of fire-related smoke incidence on air pollution given substantial ground-level pollution monitors. The spatial and temporal incidence of extreme fire and related smoke and pollution events is linked to household migration, house price, and consumer financial and credit outcomes obtained from highly articulated data sets including the Equifax Credit Risk Servicing McDash (CRISM) and the Consumer Credit (CCP) in order to evaluate household and community causal outcomes associated with wildfire events.

The analysis focuses on extreme wildfires, defined as those that damage or destroy 1,000 or more structures. Prior research has shown substantial adverse outcomes among the highest quintile of wildfires (McConnell et al. (2021), Winkler and Rouleau (2021)). Table 1 lists the 11 extreme wildfires in the U.S. between 2016-2020, 8 of which were located in California. We focus only on wildfires that occurred pre-Covid in order to cleanly differentiate between fire effects on housing and credit outcomes and those associated with COVID. Hence our study is comprised of five wildfires, including the Thomas, Carr, Campfire, LNU complex, and LNU lightning events.[5] Using a difference-in-differences approach and panel regression, we compare migration patterns, house prices, and mortgage performance in fire zones (the treatment group) with outcomes in 1- and 5-mile rings beyond the fire zone (the control group). [6] We find a significant increase in net migration among tracts that experienced the most destructive wildfires as well as a marked decrease in house prices in the quarters immediately following the fire event. Among consumer credit outcomes, we find a significant drop in the dollar balance and the number of consumer credit accounts. We also find an increase in delinquency and foreclosures among consumers in the fire zone, with a more pronounced effect for the much larger Campfire than for the four other extreme wildfires.

Next, we explore the household financial effects of smoke and air pollution emanating directly from the wildfires. A key challenge to measuring the causal effect of air pollution on credit outcomes is to identify geographically widespread fluctuations in pollution that are not themselves driven by factors that directly impact economic and financial activity. Our analysis leverages variation in air quality induced by wildfire smoke. We show that the wildfires cause marked increases in smoke and air pollution. Using satellite-based measures of daily smoke plumes for the entire U.S., we explore the effect of the wildfire-related smoke on changes in ground-level PM2.5. We use this variation

[4]Table A.1 shows the wildfires distribution in our sample. The data includes 135 wildfires between 2016-2020, 69 of them are in California, 14 in Oregon, and 9 in Florida.

[5]LNU Lightning complex happened in August 2020, but we thought it would be interesting to explore the effect of a location that experienced twice extreme wildfires in less than three years.

[6]For more information, see Appendix 2.

to provide event study evidence of the average effect of wildfire smoke on changes in air-pollution levels between zip codes experiencing fire-related smoke post fire events and zip codes not affected by smoke. We find that on average, for all five different fires, one standard deviation in the number of smoke days (11.3) is associated with an increase in pollution of 4.3 (compared to a mean of pollution levels after the fires of 9.7).[7] We proceed to estimate the relationship between air pollution from wildfire-related smoke and credit outcomes using a panel data model with fixed effects. Using quasi-experimental exposures to wildfire smoke, that analysis provides new evidence of a causal effects of wildfire-related air pollution on credit outcomes.

Our analysis estimates, for the first time, a causal relationship between air pollution and credit outcomes using quasi-experimental exposures to wildfire smoke shocks. We find that the effect of pollution on credit card balance is positive: households that were exposed to pollution levels above the 75 percentile increased their credit card balance in 63$ (compared to an average of 4,900$), on average for all the five different extreme wildfires. We also find that households exposed to changes in pollution above the 90 percentile increased their number of credit card accounts by 0.13 (compared to an average of 2.14 credit card accounts per household), on average for all the five different extreme wildfires. Our results also indicate that the effect of pollution on credit card default and mortgage default to balance is positive. We show that around the LNU complex fire, exposure to changes in pollution levels above the 90 percentiles after the fire is associated with an increase in credit card default to balance of 0.05 (compared to an average of 0.056). We also show that around the Campfire, exposure to pollution levels above the 75 percentile is associated with an increase in mortgage default of 0.0081 (compared to an average of 0.014). Exposure to pollution above the 75 percentile is associated with an increase in mortgage defaults of 0.02 (compared to an average of 0.021 in mortgage default to balance).

A number of recent papers including Issler et al. (2020) and McConnell et al. (2021) examine the effects of wildfires on mortgage and housing outcomes. Further, there are a few papers that evaluate the effect of air pollution on housing and credit outcomes. Amini et al. (2022) analyze the causal effect of air pollution on Iran's housing market by exploiting increases in air pollution due to sanctions that targeted gasoline imports and find that a 10% increase in the outdoor concentration of nitrogen dioxide leads to a decrease in housing prices of around 0.6%–0.8%. Zheng et al. (2014) use data from China and find that a 10% decrease in neighborhood pollution is associated with a 0.76% increase in local home prices, and Chay and Greenstone (2003) estimate an elasticity in the range if 0.20 to 0.35. Our analysis

[7] An analysis by Miller et al. (2021) shows an increase of PM2.5 to over 16 μg/m3 on fire-related smoke days – a level over twice the mean of a reference day. Miller et al. (2017) show that an additional day of smoke raises a county's quarterly average PM2.5 concentration by about 0.06 μg/m3.

focuses on extreme wildfires and uses more articulated data, including the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP), the CRISM dataset consisting of Equifax credit bureau data on individual consumers' credit histories matched to mortgage-level servicing data from McDash, and in some analyses, the Federal Reserve Y14 data.[8] Further, our paper is the first to augment assessment of direct effects of fire events on household economic and financial outcomes with that of indirect effects associated with fire-related air pollution.

The remainder of the paper is organized as follows. Section II describes the data and sample construction. Section III discusses the framework and empirical methodology used in the paper, whereas Sections IV present the empirical results in the paper. Section V concludes.

II. Data

A. *Data on Wildfires*

The US National Incident Management System/Incident Command System (ICS), operated by the US Department of Homeland Security, compiles information on a range of hazards notably including wildfires. While these data have been publicly available for many years, they have only recently been processed by St Denis et al. (2020) into an accessible format available for broad utilization. A major benefit of the ICS data set is that it reports direct measures of hazard impact (e.g., counts of structures destroyed or damaged), rather than the dollar value of damaged property. The latter approach, utilized by the Spatial Hazards Events and Losses Database for the United States and the NOAA National Centers for Environmental Information, fails to distinguish between widespread fire-related structural damage and that to a small number of high value properties. The ICS data provide insights important to assessment of household financial impacts of wildfire disaster (for more information, see McConnell et al. (2021)). For purposes of this study, we linked the ICS data to the Monitoring Trends in Burn Severity database (MTBS), which documents the spatial footprint of wildfire burn perimeters (Eidenshink et al. (2007)). For sampled fire events, we identify the Census blocks/tracts/zipcodes included in the fire burn perimeter and beyond. We focus on wildfires that damaged or destroyed in excess of 1,000 structures (for a list of extreme wildfires, see Table 1). Those fires account for roughly 3 percent of all wildfires.

[8] The Y14 data consists of information on loan facilities with over $1 million in committed amount, held in the portfolios of bank holding companies (BHCs) subject to the Dodd-Frank Act Stress Tests.

B. *Wildfire Smoke Data*

Measures of daily smoke exposure were developed by Miller et al. (2021) using analysis of wildfire smoke produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS).[9] The HMS uses observations from the Geostationary Operational Environmental Satellite, which produces imagery at a 1-km resolution for visual bands and a 2-km resolution for infrared bands, to identify fire and smoke emissions over the contiguous United States (Ruminski et al., 2006). Smoke analysts process the satellite data to draw geo-referenced polygons that represent the spatial extent of wildfire smoke plumes detected each day. Plumes are typically drawn twice per day, once shortly before sunrise and once shortly after sunset. We similarly employ the HMS smoke plume data from 2016 to 2020 to construct an indicator of smoke exposure at the tract level for each day of the sample period. Our primary measure of smoke exposure is an indicator of whether a tract is fully covered by a smoke plume on a given day.

C. *Pollution Data*

We obtain ambient air pollution data from the EPA's Air Quality System. We use daily ground monitor readings for EPA "criteria pollutants" including a measure of particulate matter (PM2.5). To measure air pollution for a tract, we take the distance-weighted average of two or three valid readings for each pollutant from monitors closest to tract's centroid. We spatially intersect this data with census tract boundary files and link it to individual-level administrative records. Appendixes A.1, A.2, and A.3 show the changes in wildfire smoke and pollution levels for the 2018 Camp Fire, Carr Fire, and Thomas Fire in California in the months prior to and following the fire. Wildfire smoke plumes are an important source of air pollution and travel hundreds of miles downwind, allowing us to identify the effects of smoke exposure separately from direct economic and financial damages caused by wildfire burns.

D. *Credit, Housing, and Migration Datasets*

We measure household credit outcomes using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (CCP) data. The CCP is an individual-level quarterly panel containing detailed information on consumer liabilities, delinquencies, credit scores, and demographic and geographic characteristics. The core of the database constitutes a 5% random sample of all U.S. individuals with credit files. The database also contains information on all persons with

[9] This data comes from an operational group of National Oceanic and Atmospheric Administration (NOAA) experts who rely on satellite imageries to identify the location and the movements of every wildfire smoke plume in the US

credit files residing in the same household as the primary sampled individual. Household members are added to the sample based on the mailing address in the existing credit files. The data cover all major categories of household debt including mortgages and credit cards inclusive of number of accounts and credit defaults. For more information, see (Lee and van der Klaauw, 2010).

Our main specification explores households living in census blocks inside the fire footprint and compares their financial outcomes to households living outside the fire footprint (1 to 5 miles from the fire). Therefore, because we explored a small area (census blocks), and the CCP includes only 5% random sample of all U.S. individuals, we were concerned that we did not have enough observations. Also, CCP is limited to a quarterly frequency. Therefore, in some specifications, we use the CRISM dataset, which consists of Equifax credit bureau data on individual consumers' credit histories matched to mortgage-level servicing data from McDash. Consequently, the CRISM dataset contains credit information on individual borrowers with a mortgage. Updated monthly, CRISM is constructed by using a proprietary and confidential matching process.[10] CRISM covers about 60 percent of the U.S. mortgage market during our sample period.

E. Summary Statistics

Tables 2 and 3 report summary credit information on individuals living in the extreme wildfire zones, on average, compared to those who are living (1 - 5 miles) outside the fire zones. As shown in Table 2, individuals residing in the fire zones are older, have higher credit scores, and lower mortgage balances. As shown in Table 3, similar summary characterization is evidenced for individuals residing in the area of the Camp Fire.

III. Research Strategy

A. The Effect of Extreme Wildfires on Household Migration and House Prices

We estimate the effects of extreme wildfires on household migration, house prices, and financial outcomes using difference-in-differences specifications and at both the census tract and individual levels. We assume that trends in the

[10] In the matching process, Equifax uses anonymous fields such as original and current mortgage balance, origination date, zip code, and payment history to match each loan in the McDash dataset to a particular consumer's tradeline in the Equifax.

outcomes we measure are similar for the treated and control groups in the absence of the fire.

A.1. Census Tract-Level Difference-in-Differences Estimates of Extreme Wildfire Migration and House Price Effects

This section compares net-migration (out-migration minus in-migration) and house price changes in wildfire "treated" tracts (e.g., tracts in the burn footprint) relative to "control" tracts (e.g., tracts 1 - 5 miles from the fire perimeter) for a composite sample of all five extreme wildfires. We also present results for the Campfire, the largest wildfire to date in terms of destroyed structures (for more details, see Table 1. Eight pre-event quarters are compared to the event quarter and eight post-event quarters.

All census tract level migration and house price models employ a difference-in-differences specification that estimates the effects of wildfire structure loss on net migration and on house prices. The models take the general form:

$$Y_{i,t} = \alpha + \beta(f_{i,t} * p_{i,t}) + \tau_t + \zeta_i + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is a measure of migration patterns or house prices in tract t in quarter i, which is defined as the total number of out-migrants minus in-migrants divided by the total population at the start of a period within a tract. $f_{i,t}$ represents a fire loss indicator (1 or 0), $p_{i,t}$ represents a post-fire indicator (1 or 0), and $\varepsilon_{i,t}$ represents residual errors. The interaction between these variables is the primary term of interest, where a significant coefficient indicates that net migration or house price changes associated with fire-affected units is significantly different in the post-fire period relative to outcomes in neighboring control tracts. We also include quarter fixed effects and tract fixed effects to account for unobserved time-varying factors and for time-invariant characteristics of each spatial unit. All models report heteroskedasticity consistent robust standard errors clustered by tract.

A.2. Individual-Level Difference-in-Differences Estimates

In this section, we employ a difference-in-differences model to assess the effects of extreme fire events on households financial outcomes. We use individual-level using panel data from the Federal Reserve CCP and Equifax CRISM for eight pre-event quarters and eight post-event quarters to estimate the following model:

$$Y_{i,t} = treatment_{i,t} * afterfire_{i,t} + \tau_t + \zeta_i + \varepsilon_{it}, \tag{2}$$

where $Y_{i,t}$ is the outcome measure for individual i in time t (quarterly for CCP and monthly for CRISM). The $treatment_{i,t}$ term is a dummy variable that takes on the value of one if the individual resides in a census block in the fire zone and zero if the census block is outside the fire zone (1-mile and up to 5 miles). The categorical term $afterfire_{i,t}$ takes on the value of one after the fire event and zero prior to the event. τ_t and ζ_i are time- and geographic-fixed effects. In this specification, we can interpret the interaction term as the effect of living in a treated census block in quarter/month t relative to the fire quarter.

B. *The Effect of Smoke on Air Pollution*

We use variation in wildfire smoke exposure to identify the causal effects of transient air pollution shocks on credit outcomes. Wildfire smoke plumes are a natural source of air pollution and travel far from the wildfire event, allowing us to identify the effects of smoke exposure separately from the direct damages of wildfire burns. The smoke exposure analysis is undertaken for a more diverse set of households living upwards to 30 miles from the fire perimeter. We first present event study evidence on the average effect of wildfire smoke on local air quality, using the following event study specification:

$$PM_{2.5cd} = \sum_{\tau=-20}^{20} \beta_\tau * SmokeDay_{c,d+\tau} + \alpha_{cdayofyear} + \alpha_{censustractmonth_year} + \varepsilon_{ct}, \tag{3}$$

Figure A.4 shows the effect of smoke on pollution, using an event study 20 days before and after the Campfire, between census tracts that experienced smoke, and census tracts without smoke. As evident, in the aftermath of the Campfire, in the census tracts that experienced smoke, there was a sharp increase in pollution levels, to roughly 60 μ g=m3, equivalent to pollution levels measured in Beijing on that same day.[11]

Next, We aggregate the daily smoke exposure data to the monthly level to construct our focal independent variable, $SmokeDaysMonth_{z,t}$, and observe the effect of smoke on PM2.5 by all zip codes that are located 30 miles from the fire event. The time frame is 12 months subsequent to the fire. Using observations for each zipcode z and month-year t:

$$PM_{2.5_{z,t}} = \alpha + \beta 1 SmokeDaysMonth_{z,t} + \tau_t + \zeta_z + \varepsilon_z, \tag{4}$$

Where:

[11] According to the CDC, exposure to PM2.5 above 12 is considered risky and has negative consequences.

The key independent variable is $SmokeDaysMonth_{z,t}$, defined as the number of smoke days in month t in zip code z. The regression equation includes zip code and month-year fixed effects. In some specifications we only use annual fixed effects (instead of month-year). We also examine the effect of changes in smoke on changes in pollution, using delta smoke and pollution variables, which are calculated as the change in pollution compared to the levels of pollution experienced in the same month in 2015.

C. *The Effect of Air Pollution on Credit Outcomes*

In this section, we employ a difference-in-differences model to assess the effects of pollution levels and pollution increments on household financial outcomes. We focus on zip codes located 30 miles from the five different fires and explore eight quarters after each fire. We divide the sample to focus on those who experienced pollution levels in excess of the 75 and 90 percentiles subsequent to the fire and estimate the following model:

$$Y_{i,t} = HighPollution_{i,t} * afterfire_{i,t} + X_{i,t} + \tau_t + \zeta_z + \varepsilon_z, \quad (5)$$

Where Y is the outcome measure for individual i in time t (quarterly for CCP and monthly for CRISM). The $HighPollution_{i,t}$ is a dummy variable that takes on the value of one if the individual resides in an area that experiences pollution levels above 75 or 90 percentiles and zero if not. The categorical term $afterfire$ takes on the value of one after the fire event and zero before the event, two years before and after. $\tau_t t$ and ζ_z are time- and geographic-fixed effects.

IV. Results

A. *The Effect of Extreme Wildfires on Net-Migration and House Prices*

Table 4 reports on census tract level difference-in-differences estimates of the effect of the 2018 Camp Fire on house prices. Findings indicate that the Camp Fire caused a 17 percent decline in house prices in the fire zone compared to control census tracts some 6 quarters subsequent to the fire event. In dollar value, Table 4 also shows that the Camp Fire caused a decline of 37,437$ (compared to a median repeated sales value of 280,007$ in the treated Camp Fire area). Column 4 in Table 4 shows a significant increase in residential properties vacancy rates.

The extreme wildfire event may similarly result in net-migration from affected areas. Table 5 presents results of estimation of the effect of the Camp fire on in- and out-migration from the affected area. The Camp Fire occurred in Butte County, California and destroyed more than 18,000 buildings within the town of Paradise and the surrounding unincorporated areas of Magalia, Concow, and Yankee Hill. That fire to date is the most extreme of US wildfire events, having destroyed more than twice the number of structures as any of the extreme wildfires in our sample (See Table 1). Here we compare treated fire census tracts to control tracts 1-to 5 miles from the fire. Overall, while the Camp Fire did not appear to have a significant effect on in-migration, findings indicate a substantial depressive effect on out-migration. The effect of the Camp fire on net migration is much more significant than the average net-migration effect estimated for all five extreme fires as presented in Table 6, even upon controlling for household characteristics (column 6). The results are consistent with previous research on the effect of the Camp fire (Issler et al. (2020), McConnell et al. (2021)).

We further explore the time dynamic of estimated fire-related migration effects. Figure A.6 shows migration patterns eight quarters prior and subsequent to an extreme fire event for sampled extreme wildfires including the Camp Fire, the Central LNU Complex Fire, the Thomas Fire, and the Carr Fire. These large wildfires all occurred in California during 2017-2018. As shown in the chart, the most significant change in the number of net migration (out-migration minus in-migration), was evidenced in the aftermath of the Camp Fire. We find that burned census tracts saw an additional 4 out-migrants per 100 residents, relative to their unaffected neighboring tracts (up to 5 miles), in the quarter after the Camp Fire. As evidenced in the time-dynamic for the Camp Fire, net out-migration from treated Camp Fire tracts reverted to pre-fire equilibrium levels roughly one year after the fire event. Figure A.5 shows that the adverse effects of Camp Fire on house prices and out-migration is substantial in the first few quarters following the fire but then largely reverts to pre-fire levels in subsequent quarters.

Table 6 presents findings of estimation of the effect of wildfire on net-migration for our larger sample of extreme wildfire events. We compare wildfire treated tracts (e.g., tracts within the burn footprint) to control tracts for the composite of all five extreme wildfire events in our sample. The first column in Table 6 compares the fire zone to tracts 1 - 5 miles from the fire, column 2 compares the fire zone to census tracts that are from 1 - 10 miles from the fire, and column 3 compares tracts in the fire zone to those 1 - 20 miles from the fire. Overall, findings indicate that extreme wildfires are associated with sizable and significant net out-migration among residents of surrounding control zones. The estimated migration effects are larger among control census tracts proximate to the fire treatment area and decline monotonically with distance from the fire zone. Fire-affected census tracts experienced an additional 9 net exits per

1,000 residents relative to neighboring tracts (up to 5 miles) in the two-year period following the fire ($p < .001$, SE = .003). McConnell et al. (2021) similarly found that among the top 5 percent most destructive wildfires, wildfire damage resulted in out-migration of residents. The results also are consistent with prior research on a smaller subset of FEMA disaster-declared wildfires (Winkler and Rouleau, 2021).

Our findings on migration response to extreme wildfire events add to numerous papers showing similar population moves in the wake of other climate-related natural disasters. Indeed, a growing literature identifies migration as among the most consequential outcomes of and adaptive mechanisms to climate change (Black et al., 2011). Among papers focused on the U.S., Mullins and Bharadwaj (2021) apply IRS county place-to-place data for the 1983-2017 period and find that each additional day of mean temperature between 80-90F increases annual out-migration of households by 0.43% relative to a day with a mean temperature between 60-70F, while a single additional day>90F increases yearly outgoing migration by 0.96%. Boustan et al. (2012) estimated the long-run U.S. migration response to natural disasters and found significant reductions to in-migration to counties struck by floods and hurricanes. Gallagher and Hartley (2017) estimated an elevated out-migration response and only partial subsequent return among New Orleans residents that experienced higher levels of flooding in the wake of Hurricane Katrina. Bleemer and van der Klaauw (2019) and Deryugina et al. (2018) similarly found large and persistent effects of Hurricane Katrina on movement of New Orleans residents from the city.

B. The Effect of Extreme Wildfires on Credit Outcomes

To explore the effect of extreme wildfires on financial outcomes, we use two different datasets: the Federal Reserve's CCP and the Equifax CRISM. The CCP is a 5% random sample of all U.S. individuals with credit files and includes an individual-level quarterly panel containing detailed information on consumer liabilities, delinquencies, and other characteristics. The primary challenge in application of this dataset is the limited number of observations in small areas pertinent to the wildfire footprint. Also, CCP is limited to a quarterly frequency. Hence, in some specifications, we use the CRISM dataset, which consists of Equifax credit bureau data on individual consumers' credit histories matched to mortgage-level servicing data from McDash. Consequently, the CRISM dataset contains monthly credit information on individual borrowers with a mortgage. Our paper is the first to use the Equifax CRISM dataset to explore the effects of wildfires.

Tables 7 and 8 provide new evidence from the CCP and CRISM datasets, respectively, on the effects of the

Camp Fire on household financial outcomes. The analysis is undertaken using the individual-level data and over a timeframe of eight quarters prior to and six quarters after the fire event. We focused on the financial decisions of only those households who were present throughout the sample period so as to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of household accounts. Finding from analysis of the CCP data indicate that the Camp Fire caused a significant 860$ (column 1) decline in credit card balance in treated areas (the fire footprint) relative to control areas (1 to 5 miles) beyond the fire zone. This result is sizable given an average 5,701$ fire zone household credit card balance prior to the fire. Similar results are shown in Table 8 using CRISM data: the Camp Fire was associated with a significant decline in credit card balance of 1,454$ (column 1) for households living in the treated areas relative to control areas.

Column 2 in Table 8 indicates that the Camp Fire resulted in a substantial and highly significant decline household balance on personal loans 5,300$ in the fire affected area (compared to an average 11,441 personal loan balance in those same areas). Column 3 in Table 8 indicates a sizable and significant increase in the first mortgage balance of 35,030$ among treated fire zone residents compared to those outside the fire zone (and given an average of 354,000$ mortgage balance in the fire zone pre-event).

Columns 3-5 in Tables 7 show a significant decline in the number of overall credit accounts, credit card accounts, and mortgage accounts, respectively, in the aftermath of the fire and in the fire zone in comparison to areas outside the fire zone. We find similar results using the CRISM data (Table 8). Finally, columns 6-8 in Table 7 and column 7 show a sizable and significant rise in default rates among the full range of credit instruments. Column 7 of Table 7, for example, shows an increase in credit card default to balance of 2.5% compared to an average of 3.8% prior to the fire and in the fire zone.

We estimate identical models for the Carr and Thomas Fire. As discussed above, those wildfires, while categorized as extreme, were associated with substantially fewer destroyed structures. Table 9 provides evidence of the effects of CARR fire on household financial outcomes. In general, findings are consistent with the Camp fire in that this extreme fire event resulted in an increase in credit card balances, a significant decline in the number of credit accounts, and a significant increase in credit default. Table 10 provides similar evidence of Thomas Fire effects on household financial outcomes. As shown in Table 10, the Thomas fire caused a decline in the number of credit card accounts and a significant increase in mortgage default. Similarly, as shown in Table 11, the LNU Fire caused a significant increase in mortgage balance, a decline in the number of accounts, and an increase in defaults. Overall, the results for the other extreme wildfires in California are consistent with those of the Camp Fire. In general, the effects of the Camp Fire on household financial outcomes are larger and more highly significant than those of other sampled wildfires and are consistent with other papers that have explored the effects of extreme wildfires (Issler et al. (2020), McConnell et al. (2021)).

Tables A.2 , A.3 , and A.4 assess household credit outcomes associated with extreme wildfire events by household characteristics. Those characteristics include housing tenure status, age, and credit score, respectively. The results provide new insights as to the socio-demographic incidence of of wildfire effects. Indeed, We find larger declines in the number of credit card accounts among renters, households below 50 in age, and those with a credit score between 720-790. We also find a more significant increase in credit default rates post-wildfire among renters, those aged 50 - 70, and lower credit score households.

Our findings of elevated credit default rates in the aftermath of extreme wildfire events is consistent with findings associated with other climate events. For example, Billings et al. (2022) find that credit-constrained homeowners in flooded blocks relative to those in non-flooded blocks experienced a 20% increase in bankruptcies and a 13% increase in the share of severely delinquent debt in the aftermath of Houston's 2017 Hurricane Harvey. Gallagher and Hartley (2017) study household financial outcomes associated with Hurricane Katrina and find that increases in credit card borrowing and credit delinquency rates for residents in high flood zones were small and short-lived.[12]

C. *The Effect of Smoke on Air Pollution*

Wildfires are widely recognized as major contributors to air pollution. Borgschulte et al. (2022) shows how smoke events map to ground-level air quality at the daily level, using an event study which regresses PM2.5 on a series of indicators for smoke exposure. We use similar approach, and show in Figure A.4 the effect of smoke on pollution, using an event study 20 days before and after the Campfire, between census tracts that experienced smoke, and census tracts without smoke. As evident, in the aftermath of the Campfire, in the census tracts that experienced smoke, there was a sharp increase in pollution levels, to roughly 60 μ g=m3, equivalent to pollution levels measured in Beijing on that same day. Table A.5 presents summary information for each of the California extreme wildfires on fire-related smoke and particulate air pollution (in both levels and changes in those terms compared to the same month in 2015).

[12]Deng et al. (2021) examine the relationship between temperature and residential mortgage default using weather information and loan performance data from 1996 to 2019. They find that a 1-day increase in the average monthly number of high-temperature days over the prior 12 months increases the probability of 30-day mortgage delinquency by 0.032 percentage points and the probability of home foreclosure by 0.016 percentage points.

On average, in the aftermath of the Camp Fire, for example, findings indicate five days of smoke each month and average pollution levels of 12.4. According to the CDC, exposure to PM2.5 above 12 is considered risky and has negative consequences.[13]

Table 12 shows the effect of smoke days (and changes therein) on air particulate pollution levels, controlling for zip code and year /(or month-year) fixed effects. We assess those effects twelve months subsequent to the wildfires (and separately for Camp and Thomas fires). Results of the analysis show a positive effect of smoke days in all of the various specifications. In most specifications, we find a positive and significant relationship. Column 1 in Table 12 shows that one standard deviation in the number of smoke days (11.3) is associated with an increase in pollution of 4.3 (compared to a mean of pollution levels after the fires of 9.7).[14] Column 2 shows that on average, for all five different fires, a one standard deviation increase in delta smoke (which is the change in smoke days in the same months, compared to 2015) is associated with an increase in pollution of 2.8 (compared to a mean of pollution levels after the fires of 1.3). We find a similar effects for the Camp and Thomas fires separately. Column 4 in Table 12 shows that a one standard deviation increase in smoke days in the two years after the Camp fire is associated with an increase in pollution of 6.1 (compared to a mean of pollution after the Camp fire of 12.4). Also, column 8 in Table 12 shows that a one standard deviation increase in smoke days in the two years after the Thomas fire is associated with an increase in pollution of 0.5 (compared to a mean of pollution after the Thomas fire of 6.8).[15]

D. *The Effect of Air Pollution on Credit Outcomes*

In this section, we explore the effect of changes in air pollution associated with wildfire smoke on credit outcomes. First, it is important to note that damage associated with extreme wildfires is typically widespread among households in the area of the fire footprint. Households in the fire perimeter, however, represent only a fraction of those outside of the fire area affected by fire-related smoke and pollution. Hence, the fire-related change in air pollution has the potential to impact a much larger number of households. Further, among the most widely documented adverse effects of ambient air pollution are those associated with health, inclusive of increases in hospitalization rates and premature

[13]Burke et al. (2022) find that since 2016, wildfire smoke has significantly slowed or reversed previous improvements in average annual PM2.5 concentrations in two-thirds of US states, eroding 23% of previous gains on average in those states and over 50% in multiple western states.

[14]Borgschulte et al. (2022) find that an average smoke day increases PM2:5 by 2.2 μg=m3 on the day of exposure, about one-third of a standard deviation in the distribution of daily particulate matter.

[15]One possible explanation for the low levels of smoke and pollution after the Thomas fire is the relatively open topography and proximity to ocean of the burn parimeter.

mortality among children and the elderly (Chay and Greenstone (2003), Jayachandran (2009), Chen et al. (2013), Deryugina et al. (2019), Anderson (2020)). Air pollution exposure may also reduce labor supply and productivity (Borgschulte et al. (2022), Zivin and Neidell (2012), Hanna and Oliva (2015)).[16] Chang et al. (2019) study call center workers in a large urban city in China and find that a 10 unit increase in the city's daily Air Pollution Index leads to a decrease of 0.35 percent in worker output. Adhvaryu et al. (2019) study the effects on garment manufacturing workers in India, showing each 10 unit increase in hourly PM2.5 reduces worker output by 0.5 percent. Given prior evidence of an adverse effect of air pollution on labor earnings, we assess in this section the effect of a fire-related increase in air pollution on credit balance and credit default.

Table 13 shows the effect of pollution on credit card balance, as presented in equation 5. The first two columns show the effect of pollution on credit card balance on average for all the fires. Column 1 in Table 13 indicates that households exposed to pollution above the 75 percentile level increased their credit card balance in 63$ (compared to an average of 4,900$). However, there exists variation in the effect of air pollution on credit card balance by extreme wildfire: The Camp Fire (column 3) was associated with an increase in the credit balance of 290$ (compared to an average of 3,900). In contrast, we find an insignificant decline in credit card balance for the Carr and LNU fires. Column 6 presents the results of being exposed to changes in pollution levels above the 90 percentile (compared to 2015 levels) on credit card balance for households living up to 30 miles farther from the Carr fire. Results indicate an increase in the credit balance of 570$ (compared to an average of 4,800$).

Table 14 shows the effect of pollution on the number of credit card accounts. Column 1 in Table 14 shows that households exposed to changes in pollution above the 90 percentile increased their number of credit card accounts by 0.13 (compared to an average of 2.14 credit card accounts per household). As above, results indicate variation in the effect of air pollution on credit card accounts by extreme wildfire. For example, changes in the pollution associated with the LNU complex fire have no significant impact on the number of credit card accounts. Column 5 shows that household exposure to pollution levels above the 75 percentile has only limited effect on the number of credit card accounts.

Table 15 shows the effect of pollution on credit card default to balance. The effect is positive across specifications

[16] Borgschulte et al. (2022) find that each day of wildfire smoke exposure in a county reduces per capita earnings by $5.20 in the quarter, which represents a 0.097 percent reduction from quarterly mean earnings of $5,359.70. They also find that a 1 μg=m3 (approximately 10 percent) increase in quarterly PM2:5 concentrations generates losses of per capita earnings amounting to $103, or about 1.81 percent of quarterly earnings. Borgschulte et al. (2022) report that each day of wildfire smoke reduces quarterly employment in the county by 79.6 per million individuals aged 16 and over, a 0.013 percent decline relative to the sample average employment rate of 62.6 percent.

and of varying significance levels. Column 8, for example, indicates that in the wake of the LNU complex fire, exposure to changes in pollution levels above the 90 percentiles after the fire is associated with an increase in credit card default to balance of 0.05 (compared to an average of 0.056).

Table 16 shows the effect of pollution on mortgage default to balance. Similar ro above, the estimated effect is positive in the different specifications but of varying significance levels. Column 1 shows that in the wake of the Camp Fire, exposure to pollution levels above the 75 percentile is associated with an increase in mortgage default of 0.0081 (compared to an average of 0.014). Column 3 presents similar results for the Carr fire: exposure to pollution above the 75 percentile is associated with an increase in mortgage defaults of 0.02 (compared to an average of 0.021 in mortgage default to balance). Column 5 shows that for the Thomas fire, exposure to pollution levels above the 75 percentiles after the fire is associated with an increase in mortgage default to balance of 0.015 (compared to an average of 0.013). Column 10 shows that in for the LNU Lightening Complex fire, exposure to changes in pollution levels above the 90 percentile in the wake of the fire is associated with an increase in mortgage default to balance of 0.02 (compared to an average of 0.007).

V. Conclusions and Discussion

Despite the growing impact of extreme wildfire events, there is limited evidence of their effects on household economic and financial well-being. Our paper is one of first to study the effect of extreme wildfires and related particulate pollution on household economic and financial outcomes. The analysis is based on exhaustive and geographically-precise informative from the US National Incident Command System Incident Status Summary Forms on all wildfires causing at least some structural damage (St Denis et al. (2020)). The analysis focuses on extreme wildfires, defined as those that damage or destroy 1,000 or more structures. Using a difference-in-differences approach and panel regression, we compare migration patterns, house prices, and mortgage performance in fire zones (the treatment group) with outcomes in 1- and 5-mile rings beyond the fire zone (the control group). We find a significant increase in net migration among tracts that experienced the most destructive wildfires as well as a marked decrease in house prices in the quarters immediately following the fire event. Among consumer credit outcomes, we find a significant drop in the dollar balance and the number of consumer credit accounts. We also find an increase in delinquency and foreclosures among consumers in the fire zone, with a more pronounced effect for the much larger Campfire than for the four other extreme wildfires.

Next, our analysis estimates, for the first time, a causal concentration-response relationship between air pollution and financial outcomes using quasi-experimental exposures to wildfire smoke. Wildfires emit large amounts of smoke that contain harmful pollutants and can drift for hundreds of miles, often affecting populations far from the fires themselves. We explore the household financial effects of smoke and air pollution emanating directly from the wildfires. A key challenge to measuring the causal effect of fire-related air pollution on credit outcomes is to identify geographically widespread fluctuations in pollution that are not themselves driven by factors that directly impact economic and financial activity. Our analysis leverages variation in air quality induced by wildfire smoke. Using satellite-based measures of daily smoke plumes for the entire U.S., we explore the effect of the wildfire-related smoke on changes in ground-level PM2.5. We use this variation to provide event study evidence of the average effect of wildfire smoke on changes in air-pollution levels between zip codes experiencing fire-related smoke post fire events and zip codes not affected by smoke. We proceed to estimate the relationship between air pollution from wildfire-related smoke and credit outcomes using a panel data model with fixed effects. Using quasi-experimental exposures to wildfire smoke, that analysis provides new evidence of a causal effects of wildfire-related air pollution on credit outcomes. Exposure to pollution levels above the 75 percentile caused households to increase their credit card balances in 63$ (compared to an average of 4,900$). Households exposed to changes in pollution above the 90 percentile increased their number of credit card accounts by 0.13 (compared to an average of 2.14 credit card accounts per household). We also find that the effect of pollution on credit card default to balance is positive. After the LNU complex fire, exposure to changes in pollution levels above the 90 percentile is associated with an increase in credit card default to balance of 0.05 (compared to an average of 0.056). The effect of pollution on mortgage default to balance is also positive: in the case of the Camp Fire, exposure to pollution levels above the 75 percentile is associated with an increase in mortgage default of 0.0081 (compared to an average of 0.014). Overall, findings indicate widespread direct and indirect effects of extreme wildfire and related particulate air pollution on housing economic and financial outcomes.

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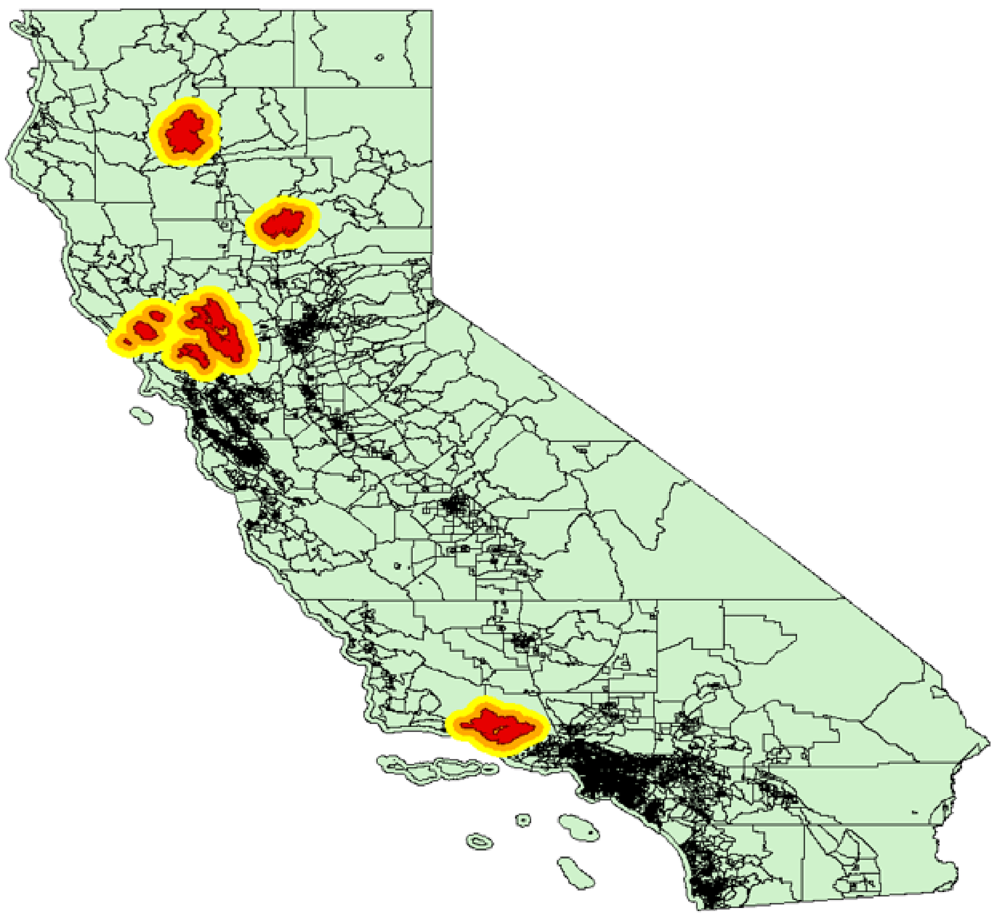


Figure 1. Extreme Wildfires in CA between 2016-2020 and the 1 and 5 miles peripheral rings
Notes: This figure shows the geographic location of the extreme wildfires (with more than 1,000 destroyed structures) in CA between 2016-2020. The red area is the fire footprint; the brown area is a 1-mile peripheral ring; the orange area is the orange ring, and the yellow ring is 10 miles from the fire.

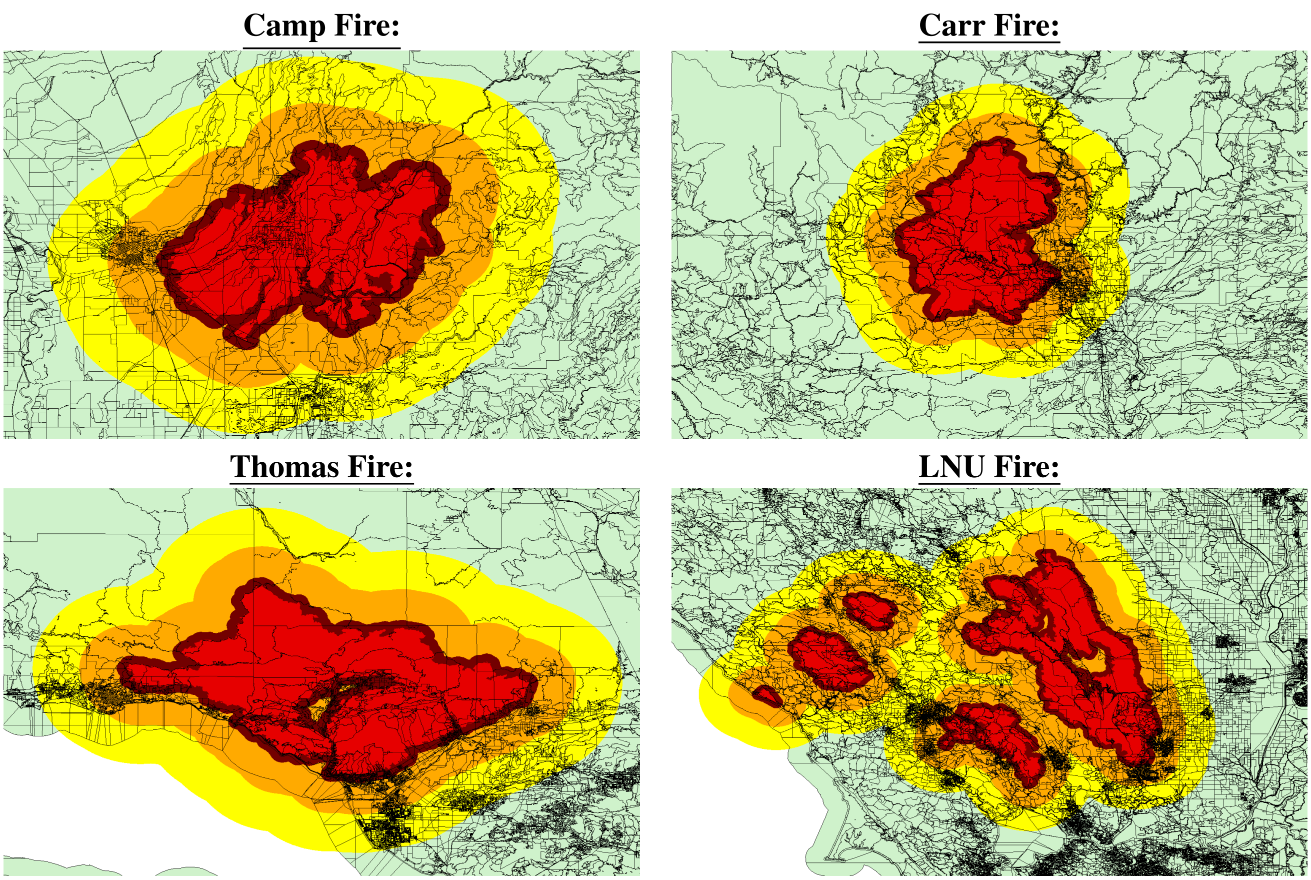


Figure 2. Extreme Wildfires in CA between 2016-2020 and the 1 and 5 miles peripheral rings

Notes: This figure shows the geographic location of the extreme wildfires (with more than 1,000 destroyed structures) in CA between 2016-2020. The red area is the fire footprint; the brown area is a 1-mile peripheral ring; the orange area is 5 miles peripheral ring, and the yellow ring is 10 miles from the fire. The border lines are census blocks in California.

Table 1. List of Extreme Wildfires in the U.S. Between 2016-2020

Fire Name	Destroyed Structures	Date	State
Camp	17,764	11/8/2018	CA
Central LNU Complex	6,862	10/9/2017	CA
Glendale	3,000	1/29/2016	OK
North Complex	2,288	8/17/2020	CA
Chimney Tops	2,018	11/23/2016	TN
Carr	1,610	7/23/2018	CA
LNU Lightning Complex	1,469	8/17/2020	CA
CZU AUG Lightning	1,329	8/16/2020	CA
Beachie Creek	1,292	8/16/2020	OR
Glass	1,198	9/27/2020	CA
Thomas	1,053	12/4/2017	CA

Notes: This table lists all the extreme wildfires (destroyed over 1,000 structures) in the United States in 2016-2020. The table also includes the number of destroyed structures, the date, and each fire's location (state). Data on the location and destruction of the fires has been processed by St Denis et al. (2020), using information from the US National Incident Management System/Incident Command System (ICS).

Table 2. Descriptive Statistics

Variable	Fire Zone			Outside Fire Zone		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Total Bank Card Balnace	19,726	5,169	10,088	135,350	5,273	9,895
Personal Loan Balance	4,197	6,611	19,648	23,599	5,437	21,021
First Mortgage Balance	5,911	299,602	381,336	27,596	331,056	306,070
Credit Card Default Rate	15,249	0.04	0.17	84,248	0.04	0.17
Personal Loan Default Rate	2,511	0.07	0.25	14,459	0.08	0.26
First Mortgage Default Rate	5,911	0.02	0.13	27,596	0.01	0.12
Number Credit Card Accounts	18,890	2.02	2.06	101,697	2.06	2.14
Number Personal Loan Accounts	18,890	0.32	0.70	101,697	0.33	0.71
Number First Mortgage Accounts	18,890	0.39	0.72	101,697	0.32	0.63
Credit Score	18,747	732.55	96.21	101,019	718.09	96.81
Age	21,916	66.36	20.88	116,092	58.95	20.82

Notes: This table provides summary statistics for the samples of households living in the fire zone and those that live outside the firezone (and up to five miles). The time frame is two years before and after each of the five wildfires. The table shows the average among the five different fires, where Table 3 presents descriptive statistics only for the Camp fire, the most destructive fire. Source: Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP).

Table 3. Descriptive Statistics - Camp Fire

Variable	Fire Zone			Outside Fire Zone		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Total Bank Card Balnace	9,565	4,460	8,438	12,098	3,926	7,380
Personal Loan Balance	2,678	7,593	22,787	1,886	4,835	14,457
First Mortgage Balance	2,975	179,458	143,548	2,199	226,876	159,271
Credit Card Default Rate	8,430	0.04	0.17	7,552	0.04	0.18
Personal Loan Default Rate	1,628	0.07	0.25	1,106	0.10	0.29
First Mortgage Default Rate	2,975	0.02	0.15	2,199	0.01	0.08
Number Credit Card Accounts	10,800	1.88	2.01	9,361	1.81	1.92
Number Personal Loan Accounts	10,800	0.36	0.73	9,361	0.28	0.64
Number First Mortgage Accounts	10,800	0.33	0.63	9,361	0.29	0.60
Credit Score	10,692	722.53	100.54	9,234	714.41	99.80
Age	12,851	67.78	21.31	11,114	58.08	21.54

Notes: This table provides summary statistics for the sample households in the Campfire zone and those outside the Campfire (up to five miles). The time frame is two years before and after the Campfire (November 2018). Source: Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP).

Table 4. The Effect of 2018 Camp Fire on House Prices

	home price index	Repeat Sales Transactions	Repeat Sales Median Price	Vacant residential
1.after	87.14***	-0.313	121,483***	
	(4.656)	(1.631)	(10,960)	
1.firezone	-0.0188	-7.968***	-67,191***	
	(1.741)	(0.625)	(4,095)	
1.after#1.firezone	-17.35***	-3.129***	-37,437***	0.0924***
	(2.388)	(1.123)	(5,700)	(0.0141)
censustract FE	+	+	+	+
Quarter FE	+	+	+	+
Outcome Average	244.4	20.6	280,007	0.03

Notes: This table shows the results of difference-in-differences estimates of the effect of the 2018 Camp Fire on house prices between census tracts in the fire zone to census tracts 1 to 5 miles farther from the Campfire. Column 1 reports the effect of Campfire on the home price index, column 2 reports the effect on repeat sales transactions, column 3 on repeat sales median price, and column 4 on vacant residential properties. All estimations include location and time-fixed effects. The time frame is two years before and after each fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel and CoreLogic data.

Table 5. The Effect of the Camp Fire on In and Out Migration

VARIABLES	1 move-in	2 move-out	3 net migration	5 move-in	4 move-out	6 net migration
1.firez	0.00664**	0.00561	-0.00103	0.00697**	0.00371	-0.00326
	(0.00321)	(0.00406)	(0.00561)	(0.00287)	(0.00364)	(0.00454)
1.after#1.firez	0.00108	0.0198***	0.0188**	0.00202	0.0198***	0.0178***
	(0.00406)	(0.00449)	(0.00677)	(0.00377)	(0.00473)	(0.00609)
age				-0.000359	-0.000334	2.45e-05
				(0.000378)	(0.000933)	(0.000894)
riskscore				9.93e-05	-0.000232***	-0.000331***
				(8.09e-05)	(8.15e-05)	(9.77e-05)
censustract fe	+	+	+	+	+	+
Q-year fe	+	+	+	+	+	+
Observations	513	513	513	513	513	513
R-squared	0.493	0.463	0.141	0.494	0.469	0.151

Notes: This table shows the results of the estimation of the effect of the Campfire on in and out-migration. We compare wildfire-treated tracts (e.g., tracts within the burn footprint) to control tracts up to 1-5 miles from the fire before and after the event. The first three columns include census tracts and time fixes effects, and the last three columns also include age and credit score as controls. Columns 3 and 6 explore the effect of Campfire on net migration, defined as out-migration minus in-migration as a percentage of the population in the census tract. The time frame is two years before and after the Campfire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 6. The Effect of Extreme Wildfires on Net Migration

	(1)	(2)	(3)
		Net Migration	
1.after	-0.00627**	-0.00370**	-0.00427**
	(0.00247)	(0.00176)	(0.00205)
1.zone	-0.00185	-0.000296	-0.000411
	(0.00278)	(0.00213)	(0.00242)
1.after#1.zone 0 vs 5 miles	0.00921***		
	(0.00327)		
1.after#1.zone1 0 vs 10 miles		0.00720**	
		(0.00284)	
1.after#1.zone2 o vs 20 miles			0.00664***
			(0.00250)
Observations	1,160	1,960	1,480

Notes: This table shows the results of the estimation of the effect of wildfire on net migration for our larger sample of extreme wildfire events. We compare wildfire-treated tracts (e.g., tracts within the burn footprint) to control tracts for the composite of all five extreme wildfire events in our sample, before and after the event. The first column compares the fire zone to tracts 1 - 5 miles from the fire, column 2 compares the fire zone to census tracts that are from 1 - 10 miles from the fire, and column 3 compares tracts in the fire zone to those 1 - 20 miles from the fire. Net migration is defined as the out-migration minus in migration as a percentage of the population in the census tract. The time frame is two years before and after each fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 7. The Effect of Camp Fire on Financial Outcomes from the CCP

	1 Credit Card Balance	2 First Mortgages Balance	3 Number Bank card Trades	4 Num personal loans	5 Number First Mortgage Trades	6 Total Default to Balance	7 Bank card Default to Balance	8 personal loans Default to Balance
1.firezone1	-4,030	-74,105	0.253	-0.0334	0.0328	0.0189	0.0303*	0.0304
	(3,028)	(50,677)	(0.265)	(0.0647)	(0.0572)	(0.0247)	(0.0159)	(0.0422)
after#zone	-862.2**	3,868	-0.373***	-0.0688***	-0.119***	0.0461***	0.0252***	0.0474*
	(428.7)	(16,670)	(0.0676)	(0.0217)	(0.0184)	(0.0100)	(0.00817)	(0.0250)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+	+
Observations	20,825	6,431	87,367	87,367	87,367	71,957	71,957	11,711
R-squared	0.083	0.148	0.038	0.012	0.119	0.390	0.142	0.300

Notes: This table shows the results of the estimation of the effect of the Campfire on financial outcomes. We compare wildfire-treated census blocks (e.g., blocks within the burn footprint) to control blocks up to 1-5 miles from the fire, before and after the event. All specifications include borrowers' characteristics (age and credit score), location, and time-fixed effects. The analysis includes eight quarters prior to and six quarters after the fire event. We focused on the financial decisions of only those households who were present in the sample throughout to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of accounts. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 8. The Effect of Camp Fire on Financial Outcomes from the CRISM

	1 Credit Card Balance	2 personal loans balance	3 First Mortgage Balance	4 Bank Card Number Accounts	5 personal loan number	6 First Mortgage Number	7 default rate
1.firezone1	-4,356	6,806	-31,066	-0.751*	-0.103	0.111	0.00491
	(5,002)	(5,761)	(46,813)	(0.392)	(0.185)	(0.162)	(0.0112)
1.after#1.firezone1	-1,454**	-5,297**	35,030***	-0.209**	0.0118	-0.154***	0.0165**
	(606.2)	(2,369)	(11,450)	(0.0913)	(0.0460)	(0.0314)	(0.00795)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+
Observations	23,063	8,605	38,703	74,314	74,314	67,503	70,292
R-squared	0.101	0.119	0.117	0.056	0.023	0.067	0.124
Average Outcome	7,900	11441.16	354,202	2.67	0.39	0.99	0.02

Notes: This table shows the results of the estimation of the effect of the Campfire on financial outcomes. We compare wildfire-treated census blocks (e.g., blocks within the burn footprint) to control blocks up to 1-5 miles from the fire, before and after the event. All specifications include borrowers' characteristics (age and credit score), location, and time-fixed effects. The analysis includes 24 months prior to and 18 months after the fire event. We focused on the financial decisions of only those households who were present in the sample throughout to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of accounts. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: CRISM dataset that consists of Equifax credit bureau data on individual consumers' credit histories matched to mortgage-level servicing data from McDash.

Table 9. The Effect of Carr Fire on Financial Outcomes from the CCP

	1 Credit Card Balance	2 First Mortgages Balance	3 Number Bank card Trades	4 Num personal loans	5 Number Mortgage Trades	6 Bank card Default to Balance	7 Mortgage Default to Balance
1.firezone1	2,197	102,983	0.340	0.0740	0.191**	-0.00386	0.0176
	(1,584)	(63,747)	(0.231)	(0.0889)	(0.0900)	(0.0190)	(0.0362)
after#zone	1,152**	11,123	-0.299***	-0.0113	-0.0157	0.00174	0.0289*
	(540.1)	(46,788)	(0.0977)	(0.0441)	(0.0274)	(0.0107)	(0.0159)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+
Observations	13,699	5,396	68,183	68,183	68,183	57,087	2,619
R-squared	0.061	0.258	0.033	0.011	0.104	0.136	0.203

Notes: This table shows the results of the estimation of the effect of the Carr fire on financial outcomes. We compare wildfire-treated census blocks (e.g., blocks within the burn footprint) to control blocks up to 1-5 miles from the fire, before and after the event. All specifications include borrowers' characteristics (age and credit score), location, and time-fixed effects. The analysis includes eight quarters prior to and six quarters after the fire event. We focused on the financial decisions of only those households who were present in the sample throughout to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of accounts. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 10. The Effect of Thomas Fire on Financial Outcomes from the CCP

	1 Credit Card Balance	2 Mortgages Balance	3 Number Bank card Trades	4 Num personal loans	5 Number Mortgage Trades	6 personal loans Default to Balance	7 Mortgage Default to Balance
1.firezone1	-2,323**	114,073	-0.0435	-0.0400	-0.0319	-0.0572**	-0.00771
	(1,125)	(361,873)	(0.193)	(0.0477)	(0.0733)	(0.0251)	(0.0208)
after#zone	-322.5	-50,701	-0.0911*	-0.0310	-0.00449	0.00974	0.0219*
	(439.4)	(33,241)	(0.0512)	(0.0192)	(0.0164)	(0.0169)	(0.0130)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+
Observations	29,532	9,525	149,839	149,839	149,839	18,749	7,257
R-squared	0.044	0.207	0.032	0.026	0.113	0.291	0.229

Notes: This table shows the results of the estimation of the effect of the Thomas fire on financial outcomes. We compare wildfire-treated census blocks (e.g., blocks within the burn footprint) to control blocks up to 1-5 miles from the fire, before and after the event. All specifications include borrowers' characteristics (age and credit score), location, and time-fixed effects. The analysis includes eight quarters prior to and six quarters after the fire event. We focused on the financial decisions of only those households who were present in the sample throughout to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of accounts. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 11. The Effect of LNU COMPLEX Fire on Financial Outcomes from the CCP

	1 Credit Card Balance	2 Mortgages Balance	3 Number Bank card Trades	4 Num personal loans	5 Number Mortgage Trades	6 personal loans Default to Balance	7 Mortgage Default to Balance
1.firezone1	-70.96	48,828	0.0741	-0.112	0.133*	0.00535	-0.0126
	(1,656)	(42,584)	(0.269)	(0.0765)	(0.0800)	(0.0392)	(0.0136)
after#zone	666.9	36,582**	-0.145*	-0.0482**	-0.0135	0.00955	0.00758**
	(672.8)	(16,865)	(0.0779)	(0.0244)	(0.0184)	(0.0423)	(0.00338)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+
Observations	31,887	14,381	122,107	122,107	122,107	21,898	40,363
R-squared	0.097	0.247	0.031	0.021	0.156	0.321	0.134

Notes: This table shows the results of the estimation of the effect of the LNU COMPLEX Fire on financial outcomes. We compare wildfire-treated census blocks (e.g., blocks within the burn footprint) to control blocks up to 1-5 miles from the fire, before and after the event. All specifications include borrowers' characteristics (age and credit score), location, and time-fixed effects. The analysis includes eight quarters prior to and six quarters after the fire event. We focused on the financial decisions of only those households who were present in the sample throughout to avoid comparison of different sampled populations before and after the fire. We further controlled for the characteristics of sampled households, including their age and credit score. For the balance results, we control for the same number of accounts. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 12. The Effect of Wild Fires Smoke on Air Pollution

	1	2	3	4	5	6	7	8	9	10
	All Fires		Camp Fire				Thomas Fire			
	pm25	pm25_delta	pm25	pm25	pm25_delta	pm25_delta	pm25	pm25	pm25_delta	pm25_delta
smoke_days_monthly	0.379***		0.0517	1.145***			2.439***	1.251***		
	(0.123)		(0.0478)	(0.0421)			(0.327)	(0.126)		
smoke_delta		0.541***			0.0730	1.853***			2.086***	0.913***
		(0.139)			(0.155)	(0.146)			(0.399)	(0.120)
zipcode fe	+	+	+	+	+	+	+	+	+	+
month-year fe			+		+		+		+	
year fe	+	+		+		+		+		+
Observations	2,097,259	2,097,259	231,078	231,078	231,078	231,078	703,494	703,494	703,494	703,494
R-squared	0.377	0.394	0.962	0.626	0.948	0.610	0.789	0.545	0.771	0.487

Notes: This table shows the results of the estimation of the effect of smoke (and the change in smoke days) on pollution levels, controlling for zip code and year (or month-year) fixed effects. The time frame is twelve months after the fires (and separately for Camp and Thomas fires). We explore all zip codes that are 30 miles from each fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: measures of daily smoke exposure were developed by Miller et al. (2021) using analysis of wildfire smoke produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS). Air pollution data was obtained from the EPA's Air Quality System.

Table 13. The Effect of Pollution on Credit Card Balance

Credit Card	1	2	3	4	5	6	7	8	9	10	11	12
Balance	All Fires		Camp Fire		Carr Fire		Thomas Fire		LNU Complex		LNU Lightning	
pollution75	26.96		-42.82		121.1		3.770		37.90		39.57	
	(23.21)		(118.6)		(74.45)		(49.61)		(79.05)		(39.45)	
after#pollution75	62.79*		289.3*		-83.70		16.73		-143.3		144.8*	
	(34.32)		(150.1)		(122.6)		(55.14)		(100.7)		(74.42)	
1.pollution_delta90		-47.23		-91.05		-489.0**		-30.16		-68.32		-31.97
		(37.05)		(145.4)		(205.0)		(54.46)		(64.45)		(42.80)
after#pm_delta90		72.18		257.3		568.7**		-150.8**		-23.40		138.1**
		(66.91)		(219.5)		(228.0)		(60.02)		(149.9)		(59.59)
Borrowers Charact	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zipcode fe	+	+	+	+	+	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+	+	+	+	+	+
Observations	1,405,443	1,405,443	141,193	141,193	103,379	103,379	482,810	482,810	225,051	225,051	453,010	453,010
R-squared	0.030	0.030	0.029	0.029	0.023	0.023	0.038	0.038	0.018	0.018	0.027	0.027

Notes: This table shows the results of the estimation of the effect of air pollution on credit card balance. We compare wildfire-treated zip codes that were exposed to pollution levels above the 75 percentile (or the 90 percentile), to those with lower pollution levels, before and after the fire, controlling for zip code and year (or month-year) fixed effects. The time frame is two years before and after the fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: air pollution data were obtained from the EPA's Air Quality System, and Credit Card Balance was obtained from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 14. The Effect of Pollution on the Number of Credit Card Accounts

Number Credit Card Accounts	1	2	3	4	5	6	7	8	9	10
	Camp Fire		Carr Fire		Thomas Fire		LNU Complex		LNU Lightning	
pollution75	-0.0693		0.0844***		0.01000		0.0135		0.0140*	
	(0.0680)		(0.0270)		(0.00812)		(0.0126)		(0.00801)	
1.after#1.pollution75	0.116		-0.0966**		0.0291**		-0.00920		0.00866	
	(0.111)		(0.0358)		(0.0127)		(0.0222)		(0.0136)	
1.pollution_delta90		-0.000246		-0.0853		0.0255**		-0.00812		-0.00568
		(0.0501)		(0.108)		(0.00995)		(0.0121)		(0.00736)
1.after#1.pollution_delta90		0.134**		0.0795		-0.0193		0.0168		0.0195*
		(0.0525)		(0.112)		(0.0191)		(0.0160)		(0.0115)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zipcode fe	+	+	+	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+	+	+	+
Observations	186,029	186,029	139,231	139,231	617,427	617,427	291,785	291,785	556,170	556,170
R-squared	0.026	0.026	0.023	0.023	0.034	0.034	0.028	0.007	0.019	0.019

Notes: This table shows the results of the estimation of the effect of air pollution on the number of credit card accounts. We compare wildfire-treated zip codes that were exposed to pollution levels above the 75 percentile (or the 90 percentile), to those with lower pollution levels, before and after the fire, controlling for zip code and year (or month-year) fixed effects. The time frame is two years before and after the fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: air pollution data were obtained from the EPA's Air Quality System, and Credit Card Balance was obtained from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 15. The Effect of Pollution on Bank Card Default to Balance

Bank card Default to Balance	1	2	3	4	5	6	7	8	9	10
	Camp Fire		Carr Fire		Thomas Fire		LNU Complex		LNU Lightning	
pollution75	-0.0210		-0.000783		0.000617		0.000778		-6.50e-05	
	(0.0174)		(0.00210)		(0.00122)		(0.00136)		(0.000578)	
after#pollution75	0.0413		0.00163		-0.00113		0.00637***		0.00127	
	(0.0271)		(0.00353)		(0.00202)		(0.00219)		(0.000949)	
1.pollution_delta90		-0.0140**		-0.00766***		0.000922		-0.0514***		-0.00149
		(0.00658)		(0.00223)		(0.00103)		(0.00221)		(0.00263)
after#pm25_delta90		0.0166		0.00911***		-0.000447		0.0502***		0.00353
		(0.0107)		(0.00290)		(0.00149)		(0.00258)		(0.00290)
Borrowers Charact	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zipcode fe	+	+	+	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+	+	+	+
Observations	186,029	156,345	116,923	116,923	528,727	528,727	249,040	249,040	487,998	487,998
R-squared	0.084	0.136	0.123	0.123	0.132	0.132	0.117	0.117	0.138	0.138

Notes: This table shows the results of the estimation of the effect of air pollution on the ratio of bank card default to balance. We compare wildfire-treated zip codes that were exposed to pollution levels above the 75 percentile (or the 90 percentile), to those with lower pollution levels, before and after the fire, controlling for zip code and year (or month-year) fixed effects. The time frame is two years before and after the fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: air pollution data were obtained from the EPA's Air Quality System, and Credit Card Balance was obtained from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 16. The Effect of Pollution on Mortgage Default to Balance

Mortgage Default to Balance	1	2	3	4	5	6	7	8	9	10
	Camp Fire		Carr Fire		Thomas Fire		Central LNU Complex		LNU Lightning Complex	
pollution75	-0.00217		-0.0141**		0.00287**		0.000739		0.00269*	
	(0.00273)		(0.00544)		(0.00128)		(0.00300)		(0.00161)	
after#pollution75	0.00809**		0.0211***		0.0147***		0.00133		-0.00309	
	(0.00297)		(0.00717)		(0.00208)		(0.00502)		(0.00238)	
pollution_delta90		-0.0111*		-0.00587		-0.000938		-0.00115		-0.0163***
		(0.00616)		(0.0126)		(0.00146)		(0.00285)		(0.00586)
after#pollution_delta90		0.0106		0.00947		0.00402		0.000563		0.0207***
		(0.00646)		(0.0133)		(0.00588)		(0.0114)		(0.00646)
Borrowers Characterist	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Zipcode fe	+	+	+	+	+	+	+	+	+	+
month-year fe	+	+	+	+	+	+	+	+	+	+
Observations	49,253	49,253	27,485	42,916	193,452	193,452	89,341	89,341	172,446	172,446
R-squared	0.148	0.148	0.255	0.158	0.152	0.152	0.168	0.168	0.137	0.137

Notes: This table shows the results of the estimation of the effect of air pollution on mortgage default to balance. We compare wildfire-treated zip codes that were exposed to pollution levels above the 75 percentile (or the 90 percentile), to those with lower pollution levels, before and after the fire, controlling for zip code and year (or month-year) fixed effects. The time frame is two years before and after the fire. Standard errors clustered by census tract in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: air pollution data were obtained from the EPA's Air Quality System, and Credit Card Balance was obtained from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Appendix

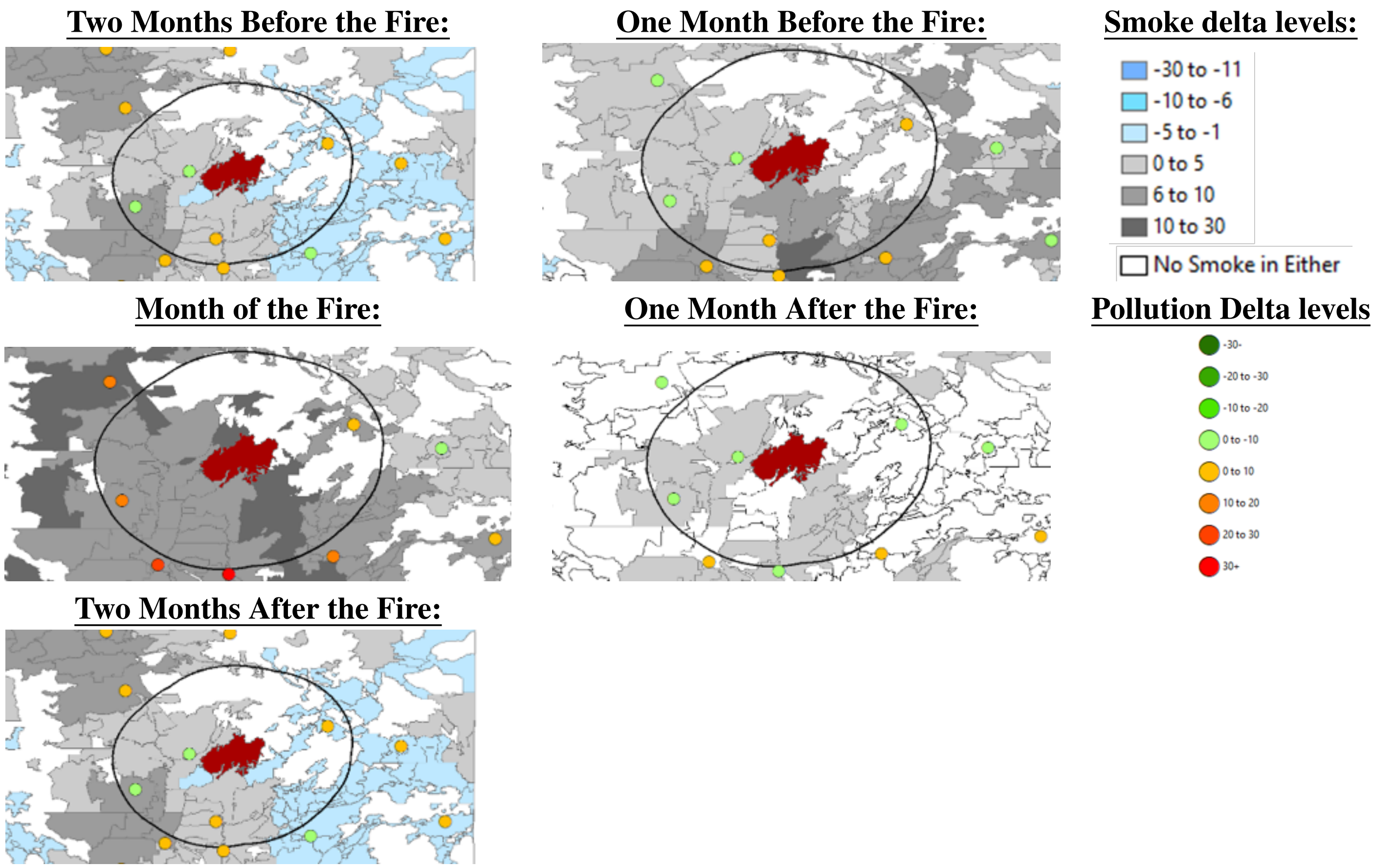


Figure A.1. Delta Smoke and Pollution - Campfire

Notes: This figure shows the variation in changes in smoke and pollution (compared to the same months in 2015) two months before and after the Campfire. The red area is the fire footprint. The black circle is a radius of 30 miles from the fire. The border lines are zip codes. Each zip code is colored in gray or blue according to the change in the number of smoke days in the current month compared to the same month in 2015 (the base year). The dots represent the pollution monitors, where the meaning of green colors represents a decline in pollution levels compared to the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared to the same month in 2015.

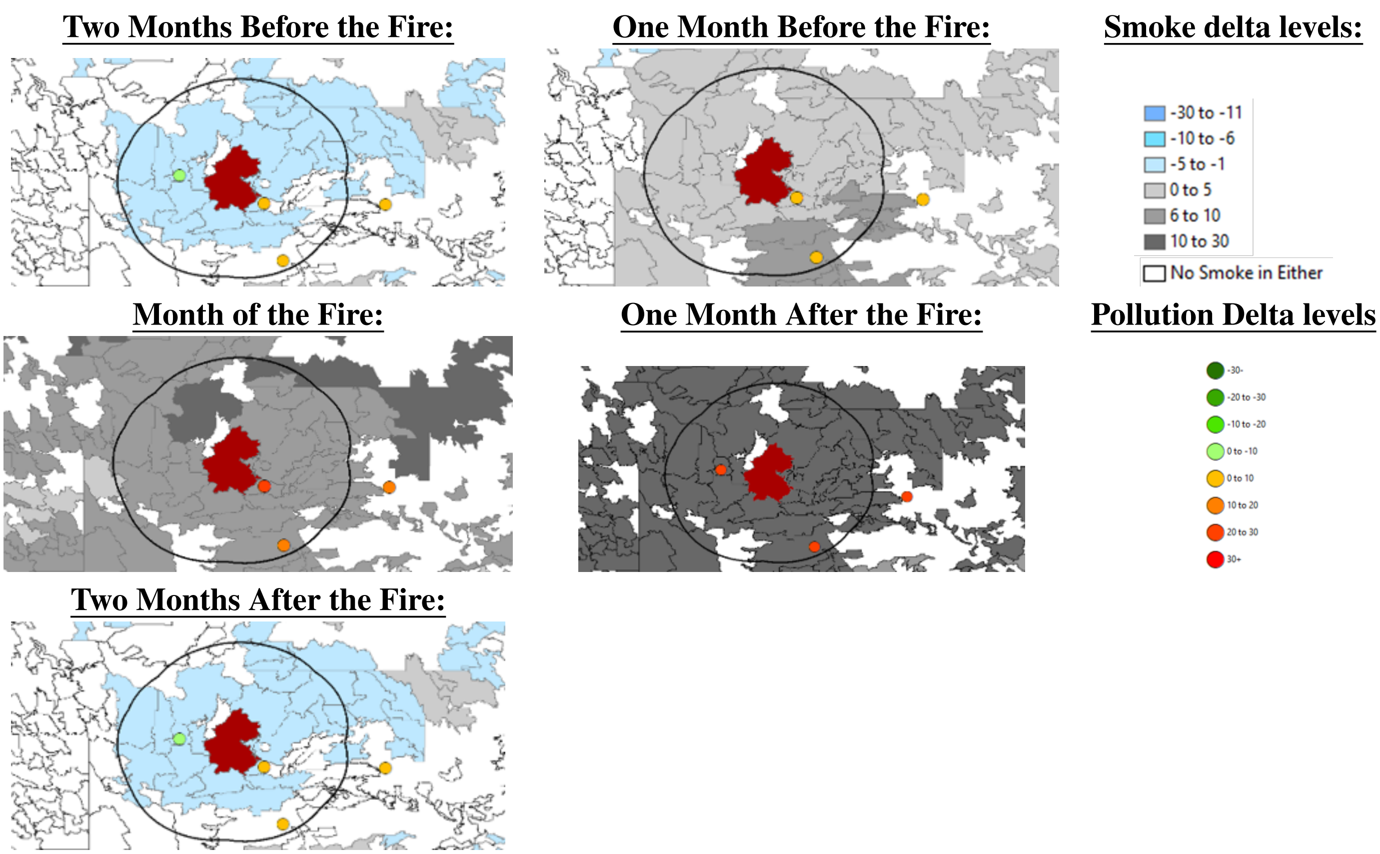


Figure A.2. Delta Smoke and Pollution - Carr Fire

Notes: This figure shows the variation in changes in smoke and pollution (compared to the same months in 2015) two months before and after the Carr fire. The red area is the Carr fire footprint. The black circle is a radius of 30 miles from the fire. The border lines are zip codes. Each zip code is colored in gray or blue according to the change in the number of smoke days in the current month compared to the same month in 2015 (the base year). The dots represent the pollution monitors, where the meaning of green colors represents a decline in pollution levels compared to the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared to the same month in 2015.

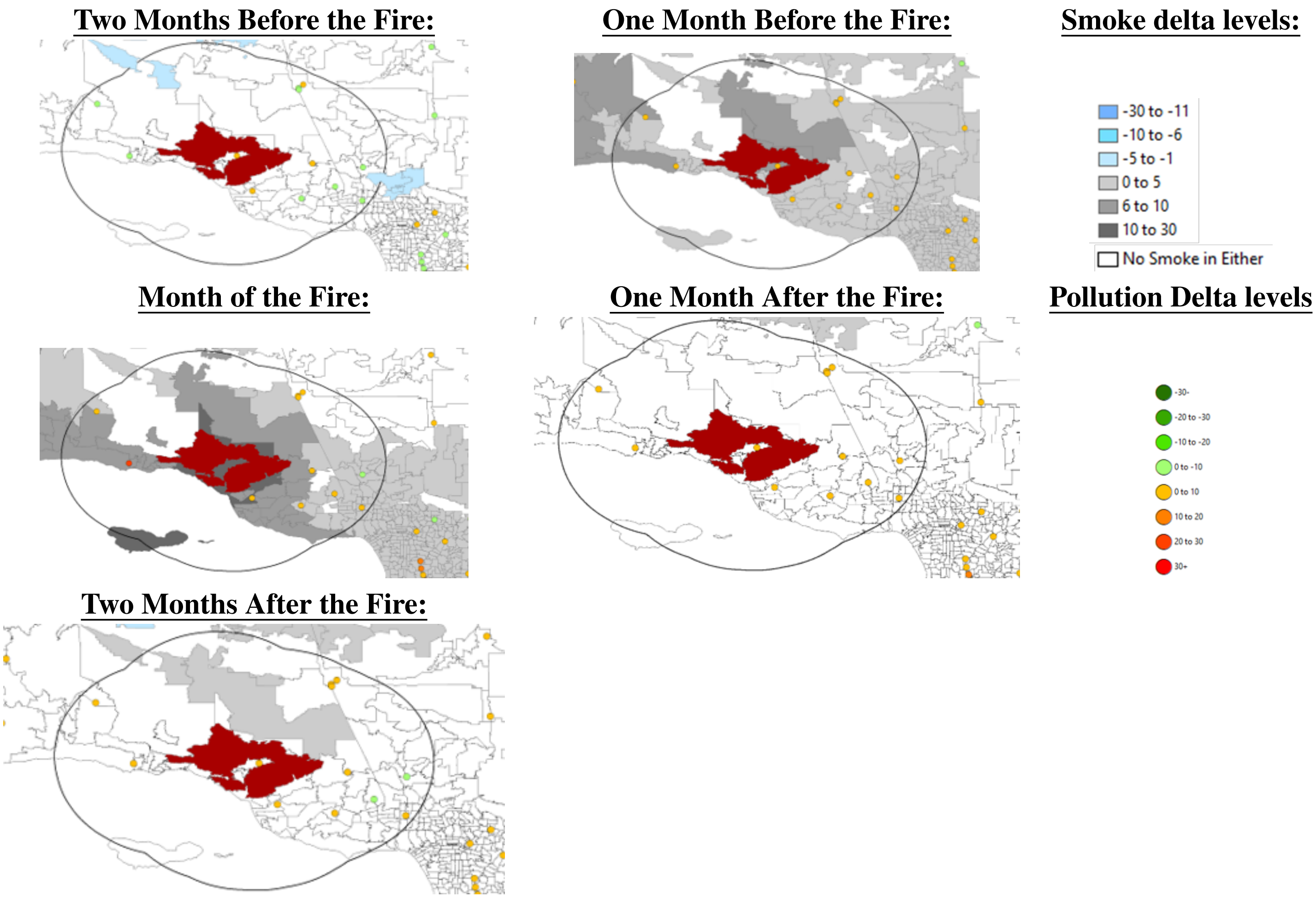


Figure A.3. Delta Smoke and Pollution - Thomas Fire

Notes: This figure shows the variation in changes in smoke and pollution (compared to the same months in 2015) two months before and after the Thomas fire. The red area is the Thomas fire footprint. The black circle is a radius of 30 miles from the fire. The border lines are zip codes. Each zip code is colored in gray or blue according to the change in the number of smoke days in the current month compared to the same month in 2015 (the base year). The dots represent the pollution monitors, where the meaning of green colors represents a decline in pollution levels compared to the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared to the same month in 2015.

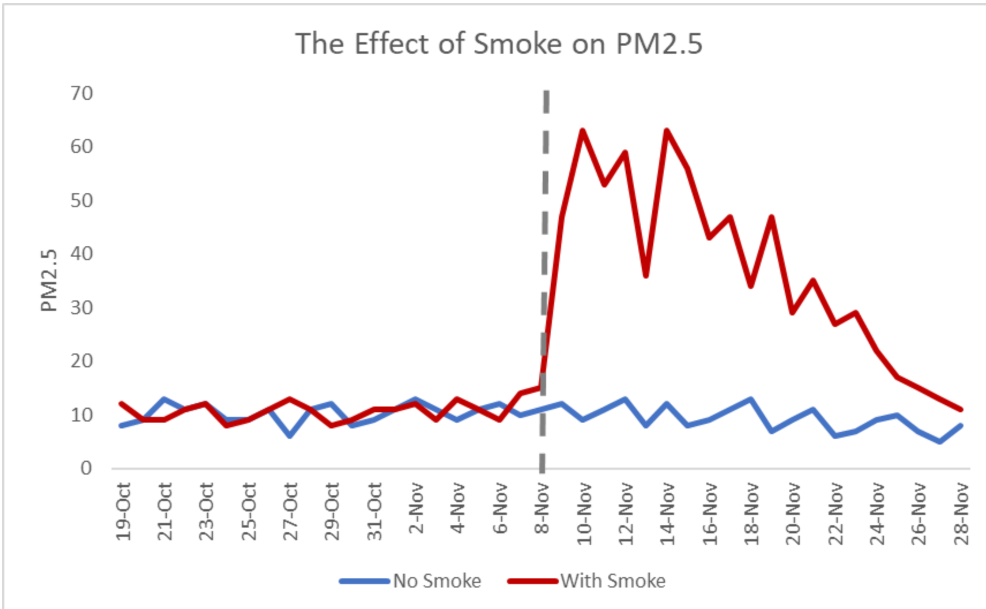


Figure A.4. Wildfire Smoke Elevated PM2.5 After the Camp Fire

Notes: This figure shows the effect of wildfire smoke on pollution levels for all the zip codes up to 30 miles from the fire perimeter, using an event study 20 days before and after the Campfire, between census tracts that experienced smoke, and census tracts without smoke, as showed in equation 3. The vertical gray line represents the start date of the Camp fire.

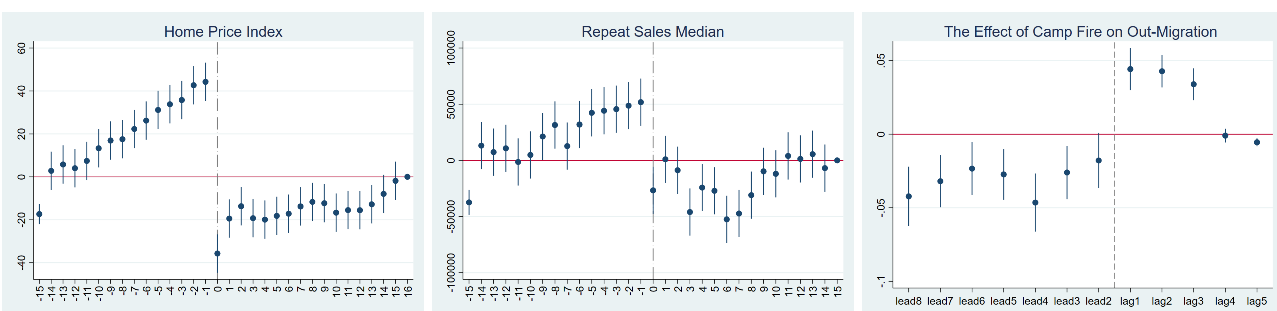
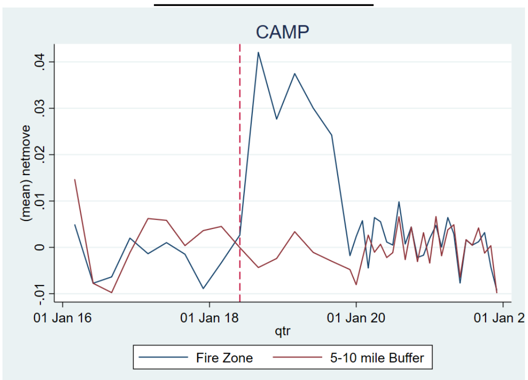


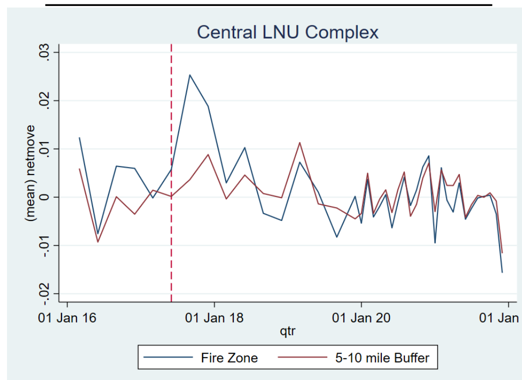
Figure A.5. The Effect of 2018 Camp Fire on Housing Prices and Out-Migration

Notes: This figure shows the time dynamic of estimated Camp fire-related house prices and out-migration effects, between households living in the fire zone, to households living in census tracts that are 1 to 5 miles from the Camp fire zone. The figure shows house prices and out-migration patterns a few quarters prior and subsequent to the Camp fire event, occurred in California during November 2018.

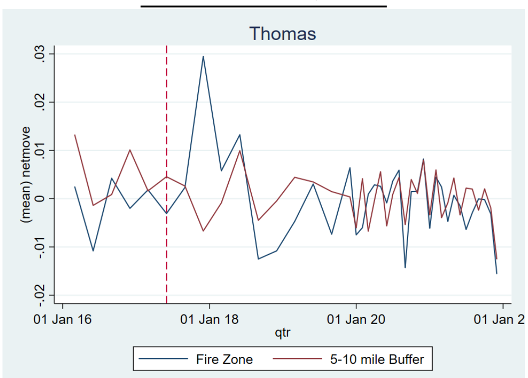
Camp Fire, CA:



Central LNU Complex Fire, CA:



Thomas Fire, CA:



Carr Fire, CA:

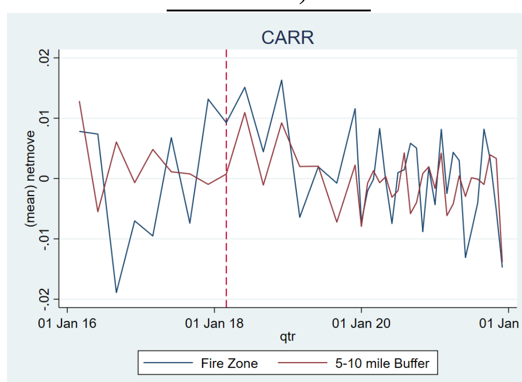


Figure A.6. Changes in Migration Patterns after Extreme Wildfires in CA between 2017-2018

Notes: This figure shows the time dynamic of estimated fire-related migration effects, between households living in the fire zone, to households living in census tracts that are 1 to 5 miles from the fire zone. The figure shows migration patterns eight quarters prior and subsequent to an extreme fire event for sampled extreme wildfires including the Camp Fire, the Central LNU Complex Fire, the Thomas Fire, and the Carr Fire. These large wildfires all occurred in California during 2017-2018.

Table A.1 . List of wildfires Across States Between 2016-2020

State	Freq	Percent	Cum.
AK	1	0.7	0.7
AZ	4	3.0	3.7
CA	69	51.1	54.8
CO	7	5.2	60.0
FL	9	6.7	66.7
ID	2	1.5	68.2
KS	1	0.7	68.9
MT	6	4.4	73.3
NV	2	1.5	74.8
OK	5	3.7	78.5
OR	14	10.4	88.9
TX	1	0.7	89.6
UT	3	2.2	91.8
WA	8	5.9	97.8
WY	3	2.2	100.0
Total	**135**	**100**	

Notes: This table shows the wildfires distribution in our sample. The data includes 135 wildfires between 2016-2020, 69 of them are in California, 14 in Oregon, and 9 in Florida. This table is based on exhaustive and geographically-precise informative from the US National Incident Command System Incident Status Summary Forms on all wildfires causing at least some structural damage (St Denis et al. (2020)).

Table A.2 . The Effect of Camp Fire on Financial Outcomes - Homeowners VS Renters

	N	1 Credit Card Balance	2 Personal Loans balance	3 Number Bank card Trades	4 Num personal loans	5 Number First Mortgage Trades	6 Bank card Default to Balance	7 personal loans Default to Balance
Homeowners	20,759	-1,707*	-3,264	-0.326**	0.0639	0.0287	0.000760	0.0132
		(921.1)	(3,672)	(0.153)	(0.0660)	(0.0518)	(0.000990)	(0.0249)
Renters	67,897	-168.6	411.3	-0.282***	-0.0548**	0.000323	0.0276***	0.0626*
		(465.1)	(2,329)	(0.0746)	(0.0225)	(0.000916)	(0.0104)	(0.0350)

Notes: This table shows the Camp fire effects on financial outcomes for homeowners and renters. ”Renters” have zero mortgage balance in all pre-Camp fire quarters. ”Homeowners” have a positive mortgage balance in all pre-Camp fire quarters. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, and St Denis et al. (2020) data.

Table A.3 . The Effect of Camp Fire on Financial Outcomes - by age

Age	N	1 Credit Card Balance	2 First Mortgage Balance	3 Bank Card Number Accounts	4 First Mortgage Number	5 default rate
Below 50	17,160	-1,471**	21,306	-0.340*	-0.153***	-0.000142
		(648.9)	(14,220)	(0.185)	(0.0467)	(0.0133)
Between 50 - 70	28,119	-1,544**	21,462	-0.105	-0.120***	0.0221*
		(717.6)	(13,991)	(0.142)	(0.0443)	(0.0118)
Above 70	18,738	-1,870**	9,163	-0.198	-0.192***	0.0225
		(915.7)	(11,979)	(0.167)	(0.0485)	(0.0149)

Notes: This table shows the Camp fire effects on financial outcomes by age group. Age is defined as 2022 minus the birth year reported in the CCP. We track households eight quarters before and Camp fire and six quarters after. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, and St Denis et al. (2020) data.

Table A.4 . The Effect of Camp Fire on Financial Outcomes - by credit score

Credit Score	N	1 Credit Card Balance	2 Personal Loans Balance	3 First Mortgage Balance	4 Bank Card Number Accounts	5 First Mortgage Number	6 default rate
Below 720	13,547	-2,325**	-3,903*	1,301	-0.234	-0.272***	0.0597**
		(1,034)	(2,102)	(11,679)	(0.191)	(0.0539)	(0.0276)
Between 720 - 790	15,606	-2,859**	814.5	20,818	-0.473**	-0.158***	0.00368
		(1,141)	(4,291)	(21,009)	(0.195)	(0.0458)	(0.00300)
Above 790	33,161	-908.9***	595.9	20,436*	-0.116	-0.0989**	-0.000226
		(345.1)	(2,534)	(12,267)	(0.137)	(0.0403)	(0.000256)

Notes: This table shows the Camp fire effects on financial outcomes by credit score. We track households eight quarters before and Camp fire and six quarters after. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel, and St Denis et al. (2020) data.

Table A.5 . Summary Statistics for Smoke and Pollution

	1	2	3	4	5	6	7	8	9
After the event	Camp Fire			Carr Fire			Thomas Fire		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
smoke_days_monthly	151,229	5.3	8.2	106,214	3.8	6.0	353,926	0.2	0.4
smoke_delta	151,229	1.3	4.7	106,214	1.1	3.4	353,926	-3.0	3.2
pm25	151,229	12.4	13.7	106,214	6.1	3.0	353,926	6.8	2.6
pm25_delta	151,229	3.7	13.1	106,214	0.9	3.1	353,926	-2.6	1.8

	10	11	12	13	14	15
After the event	Central LNU Complex			LNU Lightning Complex		
	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
smoke_days_monthly	183,419	4.3	5.3	188,416	9.4	22.6
smoke_delta	183,419	-0.3	7.0	188,416	5.3	13.1
pm25	183,419	7.7	3.4	188,416	16.6	8.9
pm25_delta	183,419	0.0	2.8	188,416	8.2	9.1

Notes: This table provides summary statistics for smoke days, pollution levels (pm2.5), and the change in smoke day and pollution levels compared to the same month in 2015, for each of the five wildfires in our paper. The time frame is eight quarters after each fire. We explore all zip codes that are 30 miles from each fire. Sources: air pollution data were obtained from the EPA's Air Quality System, and measures of daily smoke exposure were developed by Miller et al. (2021) using analysis of wildfire smoke produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS).