Extreme Wildfires, Distant Air Pollution, and Household Financial Health *

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ABSTRACT

We link detailed wildfire burn, satellite smoke plume, and ground-level pollution data to estimate the effects of extreme wildfire and associated smoke and air pollution events on housing and consumer financial outcomes. Findings provide novel evidence of elevated spending, indebtedness and loan delinquencies among households distant from the burn perimeter but exposed to high levels of wildfire-attributed smoke and air pollution. Results also show higher levels of financial distress among burn area renters, especially those with lower credit scores, while the fire effects on homeowners are less salient possibly due to insurance coverage. Out-migration as well as declines in house values are evidenced in wildfire burn area. The adverse smoke and pollution effects are salient to substantial geographically dispersed populations and add appreciably to wildfire-related financial distress estimated for households in the burn perimeter.

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I. Introduction

Recent decades have witnessed more frequent and more extreme wildfire events. U.S. wildfire events on average were four times in size, triple in frequency, and more widespread during the 2000s than in the prior two decades (Iglesias et al., 2022). Since 2000, the National Oceanic and Atmospheric Administration (NOAA) has recorded 15 wildfire events incurring damages in excess of 1 billion dollars.[1] As is well appreciated, wildfires generate smoke and air pollution that extend well beyond burn areas: In 2020, for example, smoke from wildfires fully covered US and California counties, on average, for 20 and 64 days, respectively. In June 2023, in the wake of 500 ongoing wildfire events in eastern Canada, heavy smoke and particulate emissions blanketed 122 million people across major parts of the northeast and north central United States, resulting in some of the most polluted days on record.[2] According to the Stanford ECHO Lab, the cumulative smoke exposure of the Canadian wildfires (PM2.5 exposure on each day, summed across days) through mid-2023 was substantially worse than total cumulative exposure in every year since 2006.[3] While an emerging literature has sought to document direct economic effects of climate shocks, including those pertinent to housing and financial markets (see, for example, Bernstein et al. (2019), Keys and Mulder (2020), and Bakkensen and Barrage (2017)), there has been only limited attention to the effects of extreme wildfires and related particulate emissions and air pollution on household financial outcomes. As dispersed across expansive geographies well beyond the fire zone, adverse effects of those smoke and pollution events likely are salient to household wildfire-induced distress among large populations.

Air pollution may have negative effects both on health (Deryugina et al., 2019),[4] and non-health outcomes (see Aguilar-Gomez et al. (2022) for a review). Specifically, wildfire smoke and related spikes in particulate emissions can lead to increased demand both for goods and services that mitigate deleterious air pollution effects. In fact, approximately one-third of US households have someone with existing respiratory health issues at risk of experiencing

[1]According to the NOAA, the United States has routinely spent more than $1 billion per year in recent decades to fight wildfires.

[2]On June 27 2023, the Michigan Pollution Control Agency issued its 23rd air quality alert of the year as compared to the issuance of two or three alerts in a usual year. See New York Times and Fox Weather, June 28 2023. 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]See Tweet by Marshall B Burke at Stanford ECHO Lab: https://twitter.com/marshallbburke/status/1677227498487029760?s=51&t=-2di0znAHCwH_V0x5vSv0w

[4]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).

serious medical issues with prolonged breathing of the fine particulate matter (PM2.5) found in smoke (McCaffrey and Olsen (2012)). Therefore, increased medical spending could be associated with wildfire smoke events. Smoke events may also lead to work interruption (Borgschulte et al. (2022)), increased traffic accident (Matthews (2018)), and reduced businesses in tourism and outdoor recreation (Stotts et al. (2018)), resulting in income loss and deterioration in household financial status in the immediate aftermath of the event.[5] In this paper, we assess both wildfire effects within the defined fire perimeter as well as those attributable to related particulate emissions extending to large geographies and populations well beyond the fire zone.

Our analysis is based on the combination of highly-articulated datasets on wildfires, wildfire-induced smoke plumes, attributable and localized air pollution, and consumer economic and financial outcomes. We use the US National Incident Command System Incident Status Summary Forms to identify wildfires that caused significant structural damage (St Denis et al., 2020).[6] We then apply high-resolution satellite remote sensing data to identify the locations and temporal incidence of related wildfire smoke plumes (Miller et al., 2021). We also employ daily ground monitor readings for EPA "criteria pollutants," including a measure of particulate matter (PM2.5), to measure ground level pollution as well as estimate the increment therein attributable to wildfire-related smoke. For wildfire affected populations, we compile information on housing market outcomes and migration. Further, we employ highly articulated consumer-level and loan-level datasets, including the FRBNY Consumer Credit Panel/Equifax Data (CCP); the Equifax Credit Risk Servicing McDash (CRISM)[7]; and the Federal Reserve Y-14M Capital Assessments and Stress Testing data. The granularity of the data provide unique opportunities to identify the causal impacts of wildfires and related attributable smoke and pollution.

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 US between 2016-2020, eight of which were located in California. We focus only on wildfires that occurred pre-COVID-19 in order to cleanly differentiate between fire effects on housing and credit outcomes and those associated with the pandemic. Hence, our study is comprised of four extreme wildfires—the Thomas, Carr, Camp, and LNU Complex fires. Despite the

[5]Further, long-run longitudinal studies have shown that exposure to adverse environmental conditions in early childhood can result in lower levels of educational attainment and earnings later in life (Isen et al., 2017).

[6]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.

[7]CRISM is a match between anonymous credit files from the Equifax consumer credit database and loan level mortgage data from Black Knight McDash.

growing evidence of extreme wildfire and related particulate emission events, there is limited evidence of their effects on household financial well-being.[8]

Our research design enables us to separate fire effects from those of fire-attributable smoke and air pollution. To assess fire treatment effects for households in the wildfire burn zones, we use a difference-in-differences approach in panel regression settings to compare migration patterns, house prices, credit usage and credit performance within the fire perimeter (the treatment group) with those same outcomes in 1- and 5-mile rings beyond the fire zone (the control group).[9] Figure 1 shows the geographic location of the five extreme wildfires in CA between 2016-2020, and the 1, 5, and 10 peripheral rings. In figure 2 we zoom in on the Camp fire, to better explore the fire footprint and the peripheral rings, and to show the variation within the different areas by census blocks.

Our sample design allows us to difference away smoke incidence and thus identify fire effects in this stage of the analysis (see additional discussion below). Results of the fire analyses show a significant increase in net migration from tracts that experienced the most destructive wildfires as well as a marked decrease in house prices in the quarters immediately following the fire event. We also find a near-term increase in mortgage, credit card, and personal loan delinquency rates among consumers in the fire zone, with a more pronounced effect for the much larger Camp Fire than for the three other extreme wildfires. Adverse household fire zone treatment effects usually persisted multiple quarters after the fire.

To better understand the delinquency results, we use account-level data from the Y-14M to study credit card spending, repayment and balance. Interestingly, we find that post-fire, treated households in the fire zone on average spend more but also repay credit card debt even more, resulting in a decline in balance.

The reduced credit card indebtedness (repayment in excess of spending) and increased delinquency seem to be puzzling. Further analysis shows that the reduction of credit card balance mainly happened among homeowners while increased credit card delinquencies only happened among renters, especially those with lower credit scores. Historically and during the time frame of this study, fire damage was covered by homeowner's insurance. More recently, in light of increased wildfire-related insurance payout and risk, related coverage often is excluded from the standard homeowner's insurance policy. In response, in California, the state has made limited fire coverage available via the California FAIR Plan (Biswas et al., 2023).[10] Our estimated attenuation in adverse household financial impacts includ-

[8]There has been some progress addressing these issues in recent years (Sharygin (2021), Winkler and Rouleau (2021), Issler et al. (2020), and McConnell et al. (2021)).

[9]For more information, see Figure 2. Our results are also robust to definition of control groups that are 1-2 miles from the fire zone and 1-10 miles from the fire zone.

[10]The California FAIR Plan provides basic insurance to satisfy the lender requirement that the home be insured

ing pay down in credit card balances post-wildfire among homeowners is likely due to homeowners using insurance claims payout to pay down their debt, consistent with findings from the flood disaster literature (Gallagher and Hartley (2017), Billings et al. (2022)). It is worth highlighting that, for renters who usually receive significantly less payout from fire insurance, they can experience financial distress when they needed to use their own resources to cope with the adverse fire effects such as disruption to their work and life as well possible spending to deal with health issues induced by the fire.

We then explore the household financial effects of wildfire-attributable smoke and particulate emissions diffused broadly beyond the fire zone. We first show that extreme wildfires cause marked increases in air pollution. Similar to Miller et al. (2021), we employ daily satellite-based measures of wildfire smoke plumes in a difference-in-differences framework to estimate related ground-level air pollution effects as measured by PM2.5. After establishing the causal link between smoke and air pollution, we proceed to estimate the impacts of fire-induced air pollution on credit outcomes. Again we apply a difference-in-differences framework in a panel regression setting. In an effort to assure that variations in ground level air pollution derive from fire-related smoke, we adopt two approaches. First, we create a measure of fire-attributable air pollution by taking the difference between fire month ground pollution PM2.5 levels and same month PM2.5 levels in the prior year. Second, we estimate the effects of particulate emissions using an instrumental variable approach. Due to the granularity of our data, we include consumer- or credit account-level fixed effects, so as to largely alleviate concerns of omitted variable bias.

Our results provide new evidence of adverse causal impacts of distant wildfire-induced air pollution on credit outcomes. We find significant increases in credit card spending as well as marked declines in credit card payments. Those findings are largely evidenced among zip codes well beyond the fire zone that experienced the large spikes in wildfire-induced pollution and in the quarters immediately following the wildfire event. In the five quarters following the Camp Fire, for example, the combination of added credit card spending and reduced credit card repayment among consumers experiencing high levels of wildfire-induced particulate pollution resulted in an additional $500 per annum in credit card debt. Further analyses indicate that the reduction in credit card repayment is evidenced primarily among lower credit score borrowers, consistent with the idea that those borrowers in the absence of adequate government assistance typically have fewer resources to cope with natural disasters. In contrast, the increase in credit card spending

against the risk of fire. While the FAIR Plan policy covers damage from fire, smoke, lightening, and windstorms, it does not cover other common elements of homeowners property insurance including theft, flood, earthquake, or personal liability. The California FAIR Plan coverage is typically more expensive than private policies owing to the high-concentration of high risk borrowers.

is found largely among prime borrowers. Those borrowers likely have the capacity to spend more on preventive measures to combat air pollution induced by the wildfire.

As anticipated, the estimated far-flung wildfire-attributable pollution treatment effects are smaller in magnitude than those associated for burn zone households. For example, the Camp Fire resulted in an average 45% increase in the likelihood of credit card past due among burn zone households, whereas distant wildfire-attributable emissions and particulate pollution are associated with a 20% increase in credit card past due. However, the pollution results are highly salient, given the substantially larger geographies and populations treated by far-flung wildfire-related emissions.

Three recent papers including Issler et al. (2020), McConnell et al. (2021), and Biswas et al. (2023) examine the effects of wildfires on burn zone housing and consumer outcomes.[11] We augment those studies to estimate the effects of extreme wildfires on an extensive array of household financial outcomes. For example, fire and fire-induced air pollution both cause increased delinquencies among personal loans and retail credit/store cards, not just mortgages and credit cards. We also find interesting heterogeneity in terms of the fire effects. For example, The estimated fire effects on credit cards differ among households and renters, likely owing in part to the provision of damage-related insurance payouts to households with damaged properties in the fire zone. Moreover, we provide new analyses and estimates of the far-flung effects of wildfire-related smoke and air pollution as were evidenced over broad geographies and populations beyond the burn zone. An elevated likelihood of credit delinquencies is evidenced among large numbers of distant households living beyond the burn zone. The incidence of far-flung smoke and air pollution events has become significantly more pronounced in the wake of major wildfire events in North America and Europe during the summer of 2023. Failure to account for broadly diffused and growing consequential fire emissions effects yields only a partial and incomplete picture of these extreme climatic events.

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 Section IV presents the empirical results. Section V concludes.

[11] There are a few other 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. Lopez and Tzur-Ilan (2023) analyze the effect of air pollution exposure on rent prices, using quasi-experimental exposures to wildfire smoke shocks, and find that an increase in one unit of PM2.5 reduces the average rent by 0.7%.

II. Data

A. *Data on Wildfires*

We employ information on wildfire damage compiled by the US Department of Homeland Security National Incident Management System/Incident Command System (ICS). 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 the assessment of household financial impacts of wildfire disasters (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 wildfire events, we identify the Census blocks/tracts/zipcodes included in the fire burn perimeter and beyond. We focus on extreme wildfires that damaged or destroyed more than 1,000 structures (for a list of extreme wildfires, see Table 1). Those fires account for roughly 3 percent of all wildfires.

B. *Wildfire Smoke Data*

Miller et al. (2021) developed measures of daily smoke exposure using information on wildfire smoke from the NOAA's Hazard Mapping System (HMS).[12] 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 diffusion 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.

[12]This data comes from an operational group of NOAA experts who rely on satellite imageries to identify the location and the movements of every wildfire smoke plume in the US.

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 a tract's centroid. We spatially intersect these data with census tract boundary files and link them to individual-level administrative records.

Figure 5, and Appendixes A.1, and A.2 show 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 distant effects of smoke exposure separately from wildfire damage within the burn perimeter. This paper also uses data from Childs et al. (2022), who develop a machine learning model of daily wildfire-driven PM2.5 concentrations using a combination of ground, satellite, and reanalysis data sources. The authors generate daily estimates of smoke PM2.5 over a 10 km-by-10 km grid across the contiguous US from 2006 to 2020.[13]

D. *Credit, Housing, and Migration Data*

We measure household credit outcomes using the Federal Reserve Bank of New York Consumer Credit Panel/ Equifax (CCP) data. The CCP consists of detailed credit-report data for (anonymous) individuals and households in quarterly increments beginning in 1999. The CCP is a nationally representative 5% random sample of individuals with a credit report..[14] The data cover all major categories of household debt, including mortgages and credit cards, inclusive of number of accounts, balances, and credit delinquencies. For more information, see Lee and van der Klaauw (2010).

The CCP can also be used to measure migration as we can trace individual consumers moving from one location (e.g., census tract or census block) to another in CCP using the consumer's mailing address.

CCP includes both homeowners (with and without mortgages) and renters. To contrast homeowners with renters,

[13]Childs et al. (2022) find that the number of people in locations with at least 1 day of smoke PM2.5 above 100 μg/m3 per year has increased 27-fold over the last decade, including nearly 25 million people in 2020 alone. We use this estimation to calculate the salient effect of wildfire smoke.

[14]The database also contains information on all persons with 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.

we leverage another dataset – the Credit Risk Insight Servicing McDash (CRISM) data. CRISM is an anonymous credit file match from Equifax's full population (instead of the 5% random sample) of consumer credit reports to the Black Knight McDash loan level mortgage dataset.[15] Therefore, all borrowers in CRISM are mortgage borrowers and thus homeowners. CRISM covers about 60 percent of the U.S. mortgage market during our sample period. Another advantage of the CRISM data is that it is updated monthly, instead of quarterly as for CCP.

We measure housing market outcomes mainly using the CoreLogic Home Price Index (HPI) database. The CoreLogic HPI is quarterly and available at the census region, state, Core Based Statistical Area (CBSA), county and zip code levels. We use the zip code level HPI and convert it to a census tract level HPI using the Census zip code-census tract crosswalk. The CoreLogic HPI is constructed using the weighted repeat sales methodology. In addition to the price indices, the database also includes information on the number of repeated sales used to build the index for the date period specified, and information on the median home price for repeat sales observations for the geography and period specified. The midpoint home price within the observed repeat sale home prices for the reporting period. We also used information from the U.S. Department of Housing and Urban Development (HUD) together with the United States Postal Service (USPS) on addresses identified by the USPS as having been "Vacant" or "No-Stat" in the previous quarter. We used this data to measure the changes in the share of vacant residential properties over time.

E. ***Consumer Spending Data***

To supplement the CCP data, we obtain account-level data on consumer credit card activity from the Federal Reserve Y-14M regulatory reports. In addition to being at a higher frequency, the monthly Y-14M data have an important advantage, in that they contain detailed credit card spending, payment and balance information, tracking the same accounts monthly. The Y-14M data also contain anonymized up-to-date information on the consumer and the account. Such information includes borrower contemporaneous credit score, current credit limit of the account, age of the account, contemporaneous interest rate, and borrower geographic location down to the 9-digit zip code.[16] The data also contain credit performance information including an account past due indicator. See Agarwal et al. (2020) for more information. The Y14M credit card data are available from June 2013. For our study purposes, we use data between January 2016 and December 2019, centering around the month of each wildfire in our analysis.

[15] CRISM is constructed with a proprietary and confidential matching process. 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 Equifax.

[16] Some accounts only have the 5-digit zip code.

F. Summary Statistics

Table A.2 reports summary credit information on individuals living in the wildfire zones, compared to those living (1 - 5 miles) outside the fire zones, during the six quarters before and after the fire event. Summary statistics are reported for average outcomes for the set of five sampled extreme wildfires (Camp Fire, Carr, Thomas, Central LNU Complex, and LNU Lightning Complex fires). The table shows that individuals residing in the fire zones are older, and have a higher Equifax Risk Score and lower mortgage balances. In terms of the number of credit accounts, individuals residing in the fire zones a have lower number of credit card and personal loan accounts, but a higher number of first mortgage accounts. Further, individuals residing in the fire zones are less likely to be delinquent on their personal loans, on average, but are more likely to be delinquent on their mortgage loans. Overall, individuals residing in the fire zones have lower bank card balances but higher personal loan balances, on average.

III. Research Strategy

A. Effects of Wildfires on Migration, House Prices, and Household Financial Outcomes

To assess the effects of extreme wildfires on migration, house price, and household financial outcomes, we estimate panel data models in a difference-in-differences framework at the census tract and individual consumer/account-level. Consistent with Figures 3, A.4, A.5, and A.6, we assume that trends in outcomes are similar for the treated and control groups absent the wildfires.

A.1. Census Tract-Level Difference-in-Differences Estimates of Extreme Wildfire Impacts on Migration and House Prices

We compare net-migration (out-migration minus in-migration) and house price changes in wildfire "treated" tracts (i.e., tracts within the burn area) relative to "control" tracts (e.g., tracts 1-5 miles from the fire perimeter) for the composite sample of all five extreme wildfires. We take a "donut approach" by carving out the areas that are 0-1 miles from the fire perimeter to obviate the need to assess spillover effects of the wildfires on immediate surrounding areas. We also present results for the Camp Fire, the largest wildfire to date in terms of structure loss (for more details, see Table 1). We compare pre-event quarters with post-event quarters. In the case of the November 2018 Camp Fire, we limit the analysis to eight pre-event quarters and six post-event quarters to avoid the COVID periods (starting from the first quarter of 2020), so as to cleanly differentiate between fire effects on housing and credit outcomes and those associated with COVID-19.

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

$$Y_{c,t} = \beta * Fire_{c,t} * Post_{c,t} + \tau_t + \zeta_c + \varepsilon_{c,t} \tag{1}$$

where $Y_{c,t}$ is a measure of net-migration in census tract c in quarter t, 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. $Fire_{c,t}$ represents a fire loss indicator (1 or 0), $Post_{c,t}$ represents a post-fire indicator (1 or 0), and $\varepsilon_{c,t}$ represents the error term. 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 are significantly different in the post-fire period relative to outcomes in neighboring control tracts. We also include two-way fixed effects, quarter fixed effects and census tract fixed effects, to account for unobserved time-varying factors and for time-invariant characteristics of each spatial unit. As discussed below, we undertake similar analyses of house prices. All models report heteroskedasticity consistent robust standard errors clustered by census tract.

A.2. Consumer- and Account-Level Difference-in-Differences Estimates of Extreme Wildfire Impacts on Household Financial Outcomes

We next employ similar models to assess the effects of extreme fire events on households' financial outcomes. We use consumer-level panel data from CCP and CRISM for pre- and post-event quarters to estimate the following model:

$$Y_{i,t} = \beta * Fire_{i,t} * Post_{i,t} + \tau_t + \zeta_i + \varepsilon_{it}, \tag{2}$$

where $Y_{i,t}$ is the outcome measure for individual i in time t (quarterly for CCP and monthly for CRISM). The $Fire_{i,t}$ 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 $Post_{i,t}$ takes on the value of one after the fire event and zero prior to the event. τ_t and ζ_i are time- and consumer/account-fixed effects. In this specification, we interpret the interaction term as the effect of living in a treated census block in quarter/month t relative to the fire quarter.

We also use the Federal Reserve's Y-14M data to estimate a similar panel data model in a difference-in-differences framework. As discussed above, the Y-14M data are monthly at the individual credit card account-level. More importantly, they include detailed spending and payment information, in addition to the balance and delinquency information in CCP and CRISM.

B. Effects of Wildfire Smoke and Pollution on Household Financial Outcomes

B.1. The Effect of Smoke on Air Pollution

We next turn to assessment of smoke and pollution effects. As discussed below, we use variation in wildfire smoke and related air pollution exposure to identify the causal effects of wildfire-induced shocks to air pollution 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 far flung smoke and pollution exposure as distinct from the burn zone fire effects. The pollution emissions exposure analysis is undertaken for households living up to 30 miles from the fire perimeter. We first present evidence of the average effect of wildfire smoke on local air quality using the following event study specification:

$$PM_{2.5c,d} = \sum_{\tau=-20}^{20} \beta_\tau * SmokeDay_{c,d+\tau} + \alpha_{c,day-of-year} + \alpha_{c,month-year} + \varepsilon_{c,d}, \tag{3}$$

Figure A.3 shows results of an event study of the effects of smoke on air pollution among census tracts that experienced smoke and those that did not for the 20 days before and after the Camp Fire. In the aftermath of the Camp Fire, there was a sharp increase in pollution levels in the census tracts that experienced smoke-—to roughly 60 μ g=m3—-equivalent to pollution levels measured in Beijing that same day.[17]

Next, we aggregate the daily smoke exposure data to the monthly level to construct our focal independent variable and observe its effect on PM2.5 for all ZIP codes that are located 30 miles from the fire event. The timeframe extends to 12 months after the fire. Using observations for each ZIP Code z and month-year t:

$$PM_{2.5z,t} = \beta * SmokeDaysMonth_{z,t} + \tau_t + \zeta_z + \varepsilon_{z,t}, \tag{4}$$

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

where $SmokeDaysMonth_{z,t}$ is 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 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 terms, which are calculated as the changes in smoke days and pollution levels compared with the same month in 2015.

B.2. Effects of Wildfire-Induced Air Pollution on Household Financial Outcomes

To estimate the effects of wildfire-induced air pollution on household financial outcomes, we again employ panel data models in a difference-in-differences framework. To isolate the effect of broadly-diffused smoke and air pollution from that of the wildfire itself, We focus on ZIP Codes outside of the wildfire burn area but within 30 miles from the fire perimeter. We rank order zip codes surrounding each fire based on the level of pollution n the four weeks immediately following the onset of the fire and then divide those zip codes into three groups: treated zip codes are defined as those in the top quartile of particulate pollution; control zip codes are those in the bottom quartile of particulate pollution; and the remaining zip codes are excluded from the analysis. On the time dimension, we define the sample to include five to eight quarters, depending on data availability, before and after each fire. We estimate the following model:

$$Y_{i,t} = \gamma * Pollution_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}, \tag{5}$$

where $Y_{i,t}$ is the outcome measure for individual/account i at time t (quarter for CCP and month for CRISM and Y-14M). $Pollution_z$ is a dummy variable that takes on the value of one if the individual resides in zip code z that experienced pollution levels in excess of the 75th percentile within four weeks of the fire, and zero if not. The categorical term $Afterfire$ takes on the value of one after the fire event and zero prior to the event. $X_{i,t}$ are time-varying borrower characteristics such as updated borrower credit score. τ_t and ζ_i are time- and consumer/account-fixed effects.

To assure that variations in ground level air pollution derive from fire-related smoke, we adopt two approaches. Firstly, we create a measure of fire-attributable air pollution by taking the difference between fire month ground pollution PM2.5 levels and baseline PM2.5 levels, defined as the same month PM2.5 levels in the prior year (excluding any days when there was wildfire-related smoke). Hence, the regression becomes:

$$Y_{i,t} = \gamma * \Delta PM2.5_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{6}$$

We also estimate the effect of fire-induced air pollution on household financial outcomes using an instrumental variable approach. A possible instrument is the number of smoke days experienced by a zip code in a specific month. The first stage of this instrumental approach is similar to that specified in equation 4. However, here we leverage the work of Childs et al. (2022), which provides a more sophisticated approach to first-stage estimation. Childs et al. (2022) use a machine learning model to estimate smoke-driven pollutants for the contiguous U.S. from 2006 to 2020. We use their estimates of smoke PM2.5 and run the second stage of our IV regression as:

$$Y_{i,t} = \gamma * \widehat{PM2.5}_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{7}$$

Here the $\widehat{PM2.5}_z$ are the zip code-level daily estimates obtained from the Stanford University Environmental Change and Human Outcomes (ECHO) Lab [18] aggregated to monthly frequency. In order to evaluate how wildfire-induced air pollution dissipates over time, we also run event-study type of regressions in a similar difference-in-differences setting.

It is noteworthy that when we estimate the fire effects, we focus on treated areas within the fire boundary and control areas up to 5 miles from the fire perimeter. As discussed below, the entirety of the spatial footprint of the fire study (both treatment and control areas) were treated by fire-related smoke. Hence, our DID approach by design differences out the smoke/pollution effects so as to allow us to identify burn zone fire effects. In our subsequent analysis of smoke and particulate air pollution, we carve out the fire perimeter and immediate adjacent areas. Here our sample design allows us to focus on distant smoke and pollution effects 5- to 30-mile away from the fire zone.

IV. Results

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

Table 2 presents findings of estimation of the effects of extreme wildfires on household net-migration. We compare wildfire treated tracts (e.g., tracts within the burn footprint) to control tracts for the Camp Fire. The first three columns in Table 2 compare the fire zone to those 1 - 5 miles from the Camp fire. Overall, findings indicate that the Camp Fire is associated with sizable and significant net out-migration among residents of surrounding control zones. The estimated migration effects are larger among control census tracts more proximate to the fire treatment area and decline monotonically with distance from the fire zone. Columns 4 and 5 of Table 2 present results of estimation of the effect

[18] https://www.stanfordecholab.com/wildfire_smoke.

of the Camp Fire on net-migration and compare fire zone tracts to those that are from 1 - 10 miles from the fire (column 4), and column 5 compares fire zone tracts to those 1 - 20 miles from the fire. The Camp Fire occurred in November 2018 in Butte County, California and destroyed more than 18,000 buildings in the town of Paradise and surrounding unincorporated areas of Magalia, Concow, and Yankee Hill. To date, that fire is the most extreme of US wildfire events, destroying more than twice as many structures as any other sampled extreme wildfire (See Table 1). Overall, while the Camp Fire did not appear to significantly affect in-migration, findings do indicate a significant increment to out-migration. Census tracts up to 5 miles from the perimeter of the Camp Fire experienced an additional 18 net exits per 1,000 residents compared with fire zone tracts. The effect if stable even we explore areas that are farther from the Camp fire, 10 and 20 miles from the Camp Fire. We further explore the time dynamic of estimated fire-related migration effects. Figure A.4 shows that adverse effects of Camp Fire on in- and out-migration are substantial in the year following the fire; subsequently, household migratory flows then largely revert to pre-fire levels. The results are consistent with previous research on the effect of the Camp Fire (Issler et al. (2020), McConnell et al. (2021)).[19] Our findings also are consistent with prior research on a smaller subset of FEMA disaster-declared wildfires (Winkler and Rouleau, 2021).

Table 3 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 17.5 percent decline in house prices in the fire zone compared with control census tracts some six quarters subsequent to the fire event. In dollar terms, Table 3 shows that the Camp Fire caused a decline of $34,553 (compared with a median repeat sales value of $280,007 in the treated Camp Fire area). Figure A.4 further shows that house prices remained substantially damped in the year and a half following the Camp Fire but then largely reverted to pre-fire levels. That notwithstanding, that same table shows that the repeat sales median house price in the area treated by the Camp Fire remained damped by roughly $10,000 throughout the post-fire study period. Column 4 in Table 3 shows a significant increase in residential vacancy rates.

Our findings on migration response to extreme wildfire events are consistent with other papers showing similar net exit of population 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 US, Mullins and Bharadwaj (2021) apply IRS county place-to-place data for the period 1983-2017 and find that an additional day of mean temperature between 80–90F increases annual out-migration

[19] McConnell et al. (2021) similarly found that among the top 5 percent most destructive wildfires, wildfire damage resulted in out-migration of residents.

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. Effects of Extreme Wildfires on Household Financial Distress

The impact of wildfire on household financial distress is unclear a priori. On the one hand, wildfires can destroy the physical property and cause disruption to life, work and businesses. On the other hand, fire insurance through either the standard homeowners insurance or separate wildfire insurance can greatly mitigate losses to households. In addition, there could be small amounts of government aid and private donations that help mitigate the adverse fire effects. Empirical evidence in the existing literature is mixed. For example, for mortgage performance, Issler et al. (2020) find little to even positive impact. Biswas et al. (2023) find some elevated mortgage delinquencies among damaged properties in fire burn areas but no impact on non-damaged properties in the fire zone. McConnell et al. (2021) find measures of consumer credit distress, including delinquencies, bankruptcies, and foreclosures, improve rather than deteriorate after the fire, but the changes are not statistically significant.

To explore the effect of extreme wildfires on household financial distress, we first analyze the FRBNY Consumer Credit Panel/Equifax Data (CCP). The CCP is a 5% random sample of all U.S. individuals with credit files and includes a consumer-level quarterly panel containing detailed information on consumer liabilities, delinquencies, and other characteristics.

Table 4 shows the effect of the Camp Fire on consumer financial distress, estimated in a difference-in-differences framework following equation 2. Note that our treated group is consumers living in census blocks that were within the Camp fire burn footprint, while the control group includes consumers living 1-5 miles from the fire perimeter. Dependent variables in columns 1-4 are mortgage delinquency, credit card delinquency, personal loan delinquency, and retail/store card delinquency, respectively. While we find no significant result for mortgage delinquency in column 1, columns 2-4 show statistically significant effect of Camp fire on consumer credit card, personal loan, and retail/store card delinquencies. For example, Column 2 shows that consumers living in Camp Fire burn zone experienced an extra

3 percentage point (pp) increase in credit card delinquency after the Camp fire, compared to consumers not directly affected by the fire (those living 1-5 miles from the fire perimeter). This effect is also economically significant given that the average credit card delinquency rate is about 4 percent in our sample. In Column 4, we see that consumers living in Camp Fire burn zone experienced an extra 6 percentage point (pp) increase in retail/store card delinquency after the Camp fire, which is 50% of the average retail/store card delinquency rate (12 percent) in our sample. In all these regressions, we include year-quarter fixed effects and census tract fixed effects and control for time-varying borrower characteristics such as borrower age and updated credit score.

Results in Table 4 are average treatment effects in the eight quarters after the Camp fire. In Figure 3, we plot the quarter-by-quarter effects of the fire, estimated with a similar difference-in-differences approach. Panels A-D show estimated effects on consumer total delinquency (delinquencies across all credit accounts), credit card delinquency, retail/store card delinquency, and mortgage delinquency, respectively. These results show that the fire effects on credit card and retail/store card delinquencies persisted through out the two year post-fire periods.

To better understand the significant fire effect on credit delinquencies, we next turn to the Federal Reserve Y-14M data for credit cards. An advantage of the Y14M credit card data is that we observe in the data not only delinquencies but also credit card spending, repayment, and balance every month at the account level. We follow the same difference-in-differences approach in estimating the fire effect using the account-month panel. The granularity of our data allow us to include two-way fixed effects. In addition, we control for time-varying account attributes such as updated borrower credit score and current credit limit of the account.

In Table 5, we report our estimates of the effects of the Camp Fire on credit card spending, payment, balance, and past due in columns 1-4, respectively. To account for possible seasonality, we use year-over-year changes for our dependent variables. Changes in credit card spending, repayment, and balance, as shown in the first three columns, are annualized dollar amounts. Estimates in the table show that borrowers residing in the wildfire burn area engaged in roughly \$1,100 per annum additional spending in the 14 months after the fire, compared with borrowers residing 1 - 5 miles outside the burn area (column 1). Interestingly, estimates also show about \$1,500 per annum increase in repayment, relative to those outside of the fire burn zone (column 2). As a result, households living within the wildfire burn perimeter accumulated an estimated \$1,900 per annum less credit card debt (column 3). Column 4 of Table 5 show elevated account past due among borrowers residing in the wildfire burn area, consistent with the increased credit card delinquency result we see from the CCP analysis discussed previously.

In Figure 4, we plot our estimated effects of the Camp Fire on credit card spending and repayment quarter-over-quarter. We see a clear increase in credit card spending and repayment right after the fire among those residing in the fire zone. The increases in spending and repayment peaked in the second quarter post-fire and then tapered in quarters 3-5.

The reduced credit card indebtedness (repayment in excess of spending) and increased delinquency/past due results we see in Tables 4 and 5 do seem puzzling. In that regard, we have two hypotheses: First, we hypothesize that homeowners whose property was damaged by the fire was able to use insurance claims payout to pay off some of their debt including credit card balance. Second, those who did not receive insurance claims payout may fall into delinquency due to increased credit card spending to cope with the fire.

Unfortunately we cannot tell if a borrower is a homeowner or not in the Y-14M data. We thus return to the CCP data, and segment our sample into homeowners and renters.[20] We further separate high credit score borrowers from low credit score borrowers. We then repeat our difference-in-differences analysis with the segmented CCP sample. Table 6 report our results on credit card balance (Panel A) and credit card delinquency (Panel B).

From these results, we see that homeowners residing in the fire zone (and thus likely to have their properties damaged) did pay down their credit card balance more than those in the control group (Panel A column 2). For those consumers, we do not find any increase in credit card delinquency (Panel B columns 1 and 2). In contrast, elevated credit card delinquency comes from lower credit score renters (Panel B column 3).

These results and the results in the previous two tables paint the following picture that involves the interplay of fire damage and insurance claims payout shaping consumer financial outcomes: Camp fire caused property damage and interruptions to people's life and work; in order to cope with the adverse effect of the fire, consumers spend more using their credit cards. However, for homeowners who received insurance claims payout, some were able to use the payout to pay down their debt including credit card balance; for renters who received no or not enough insurance pay out, they couldn't make extra repayment to pay down their credit card debt and some of them even fell into delinquency.

The insurance claims payout story is not only consistent with findings in Gallagher and Hartley (2017) regarding mortgage borrowers using flood insurance payout to pay down their mortgages but also supported by additional analysis results in Appendix Figures A.5 and A.6. In Appendix Figure A.5, we see that for consumers who remained in the fire zone after the Camp fire, both their number of credit card accounts and credit card balance were reduced significantly after the fire. In Appendix Figure A.6 based on CRISM data, we see the decline in credit card accounts

[20]In CCP, we define consumers with positive mortgage balance as homeowners. By doing so, we include cash buyers/owners in the renter category, which can cause some aggregation bias in the renter analysis.

and balance was significantly bigger for mortgage borrowers in the fire zone (who owned homes in the fire zone).[21]

C. *The Effect of Smoke on Air Pollution*

Wildfires are widely recognized as major contributors to air pollution. Burke et al. (2021) estimate that wildfires have accounted for up to 25% of PM2.5 recorded in the U.S. in recent years, and as much as 50% of PM2.5 in some Western regions. Further, spatial patterns in ambient smoke exposure do not coincide with typical socioeconomic pollution exposure gradients. Borgschulte et al. (2022) show how smoke events map to ground-level air quality at the daily level, using an event study that regresses PM2.5 on a series of indicators for smoke exposure. We employ a similar approach. In Figure A.3 we show the effect of wildfire-related smoke on air pollution, using an event study of the 20 days prior to and after the Camp Fire, among census tracts that were and were not exposed to the smoke. As evident, in the aftermath of the Camp Fire, in census tracts treated by wildfire-related smoke, pollution levels increased sharply, to 60 μ g=m3, roughly equivalent to pollution levels measured in Beijing on that same day. Table A.5 presents summary information for each of the sampled California extreme wildfires on fire-related smoke and particulate air pollution (in both levels and changes in those terms compared with the same month in 2015). On average, in the aftermath of the Camp Fire, for example, findings indicate a monthly average of 5 smoke days pollution levels of 12.4. According to the CDC, exposure to PM2.5 above 12 is considered risky and has negative consequences.[22] Concerns regarding adverse effects of wildfire-attributable smoke and particulate pollution intensified in the north central and northeast U.S. in June 2023 in the wake of widespread Canadian wildfires, which adversely impacted large geographies and millions of households.

Table A.6 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 12 months subsequent to the wildfires (and separately for Camp and Thomas fires). Results of the analysis indicate a positive and significant effect in most specifications. Column 1 in Table A.6 shows that one standard deviation increase 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).[23]

[21] Borrowers in the CRISM sample are all mortgage borrowers as CRISM is a match between McDash mortgage servicing report and consumer credit report.

[22] Burke et al. (2022) find that since 2016, wildfire smoke has 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.

[23] 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.

Column 2 shows that on average, for all five fires, a one standard deviation increase in delta smoke (the change in smoke days in the same months relative to 2015) is associated with an increase in pollution of 2.8 (compared with a mean of pollution levels after the fires of 1.3). We find similar effects for the Camp and Thomas fires. Column 4 in Table A.6 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 A.6 shows that a one standard deviation increase in smoke days in the two years after the Thomas fire is associated with a pollution increase of 0.5 (compared with a mean of pollution after the Thomas fire of 6.8).[24] As is evident, the increment in particulate pollution attributable to extreme wildfires is sizable.

D. *Effects of Air Pollution on Borrower Credit Outcomes*

In this section, we explore the effect of changes in wildfire smoke-attributable air pollution on household credit outcomes. As discussed above, large geographies and populations beyond the actual burn perimeter may be treated by wildfire-attributable smoke and air pollution. Indeed, heavy smoke and pollution emissions from the 500 active Canadian wildfires in June 2023 resulted in dangerous and unhealthy air for tens of millions of households in the north central and northeast United States.

Among the most widely documented adverse effects of ambient air pollution are those associated with health, inclusive of increases in hospitalization rates and premature mortality among children and the elderly (Chay and Greenstone (2003), Jayachandran (2009), Chen et al. (2013), Deryugina et al. (2019), Anderson (2020)). Smoke events may also lead to work interruption (Borgschulte et al. (2022)), increased traffic accident (Matthews (2018)), and reduced businesses in tourism and outdoor recreation (Stotts et al. (2018)),[25] resulting in income loss and deterioration in household financial status in the immediate aftermath of the event. In fact, there is evidence showing that air pollution exposure reduce earnings. For example, 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.[26] 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 older, a 0.013 percent decline relative

[24] 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 perimeter.

[25] See, also, ”Up in Smoke: Canada’s Outdoor Summer Season,” *New York Times*, July 25, 2023.

[26] They also find that a 1 μg=m3 (approximately 10 percent) increase in quarterly PM2:5 concentrations generates losses in per capita earnings amounting to $103, or about 1.81 percent of quarterly earnings.

to the sample average employment rate of 62.6 percent.

Table 7 shows the effects of air pollution emanating from the Camp Fire on credit delinquencies among distant households, defined as those located 5-30 miles from the Camp Fire boundary. We compare consumers residing in zip codes that were exposed to pollution levels in excess of the 75 percentile of the distribution (treatment group) to those residing in zip codes with pollution levels in the bottom quartile (control group), before and after the Camp Fire. The time frame is two years prior to and 18 months after the Camp Fire (until the start of the COVID-19 pandemic). Column 1 in Panel A shows an extra one percentage point increase in the likelihood of mortgage delinquency for the treatment group after the fire. As a reference, the average mortgage delinquency rate is one percent in our sample. Columns 2 through 4 show that exposure to high levels of pollution result in an increase in credit card, personal loan, and retail/store card delinquencies. All these results are economically significant.

In Panel B of Table 7, we present results of IV estimation, as specified in equation 7. Estimates are qualitatively consistent with those shown in Panel A. Again, heavy wildfire-related air pollution results in statistically and economically significant elevation in credit and retail/store card delinquencies. We cannot estimate the effects on mortgage and personal loan delinquencies with precision with the IV approach, though.

Table 8 shows the effects of CAMP Fire-induced air pollution on credit card usage and credit performance, using the Federal Reserve Y-14M data. Panel A of the Table shows estimates of pollution effects using year-over-year changes in PM2.5 as specified in equation 6. The outcome variables include monthly measures of credit card spending, repayment, balance, and the likelihood of account past due. To account for possible seasonality, we use year-over-year changes in our dependent variables. Changes in credit card spending, repayment, and balance are computed as the annualized dollar amount. Results indicate that consumers exposed to heavy wildfire-related air pollution on average increase their spending by $389 on an annual basis, relative to those exposed to low levels of wildfire-induced air pollution. Meanwhile, repayment of credit card debt among treated households was $173 dollars less on an annual basis. As a result, treated households accumulated about $500 more in annualized credit card debt. Findings are consistent with prior results suggesting that households exposed to severe wildfire-induced air pollution spend more (e.g., owing to smoke-induced health issues) and earn less resulting in a reduced ability to repay their debt.

In terms of credit performance, those exposed to severe air pollution due to wildfires showed a 2.2% elevated likelihood of having an account past due. This finding is economically significant, given an average rate of account past due of 11.6%. While the estimated effect effect of wildfire-related pollution on household credit performance is not as large as that computed above for wildfire structural damage, bear in mind that the smoke-treated population is substantially diffused among much larger treated populations.

In Table 8 Panel B, we present results of our IV estimation, as specified in equation 7. Estimates are consistent with those shown in Panel A. Again, heavy wildfire-induced air pollution resulted in additional credit card spending and reduced repayment among treated borrowers. Borrowers exposed to heavy wildfire-induced air pollution accumulated more credit card debt and were more likely to have a credit account past due. As discussed previously, the regressions include highly granular account and year-month fixed effects. Controls further include time-varying borrower attributes such as refreshed borrower credit score and current credit limit of the credit card account.

Table 9 reports on heterogeneity in smoke effects among population stratified by credit score. Here we observe some interesting patterns. For example, estimates indicate that the reduction in credit card repayment is evidenced primarily among lower credit score borrowers, consistent with the idea that those borrowers in the absence of adequate government assistance typically have fewer resources to cope with natural disasters. In contrast, the increase in credit card spending is found largely among prime borrowers. Those borrowers likely have the capacity to spend more on preventive measures to combat air pollution induced by the wildfire. In Appendix Table A.7 , we compare our IV wildfire-induced pollution estimates across different extreme wildfires. While results vary across wildfires, they are qualitatively consistent in indicating that consumers exposed to heavy pollution spend more and repay less, compared to those exposed to low or no pollution.

Finally, in Figure 6, we plot the time-varying effects of wildfire-induced air pollution on credit card usage. In the initial quarter following a wildfire, we see a marked increment in credit card spending. The estimated effect remains elevated in the subsequent quarters but tends to dissipate over time. We also see reduced credit card repayment in the quarters after the wildfire for those who were exposed to heavy pollution.

V. Conclusions

Despite the growing incidence, severity, and geography of extreme wildfire events, there exists limited evidence of localized burn and dispersed smoke and pollution effects on household financial well-being. The latter extend well beyond fire perimeters and owe to substantial, far flung, and lingering wildfire-related smoke and particulate emissions. In this paper, we provide estimates of wildfire and attributable smoke and particulate pollution effects across a broad array of household economic and financial indicators. The analysis is based on the combination of highly-articulated datasets on wildfires, wildfire-induced smoke, air pollution, and consumer economic and financial outcomes. Using a difference-in-differences approach, we compare migration patterns, house prices, and credit usage and performance in fire zones to outcomes in 1- and 5-mile rings beyond the fire perimeter, before and after wildfire events. We find a significant increase in net migration from tracts that experienced the most destructive wildfires as well as marked declines in house prices in the quarters immediately following the fire event. Among fire zone-treated households, we also find an increase in financial distress, measured by mortgage, credit card, and personal loan delinquencies. For example, in the case of the Camp Fire, households living within the fire perimeter recorded an increase in bank credit card delinquency rates of 2% compared to an average level of 4%. Further analyses show that elevated credit card delinquencies mainly concentrated in lower credit score renters while homeowners in the burn area were able to pay off their credit card balance faster than usual, possibly due to insurance claims payout they received.

We then explore the household financial effects of wildfire-attributable but broadly-diffused smoke and air pollution events. We provide new estimates of the causal concentration-response relationship between air pollution and financial outcomes using quasi-experimental exposures to wildfire smoke. As evidenced in the 2023 Canadian wildfires, those events can emit large amounts of smoke that contain harmful pollutants and drift for hundreds of miles, often affecting substantial population far from the fire zones. Our analysis assesses variation in air quality induced by wildfire smoke. Using satellite-based measures of daily smoke plumes for the entire U.S., we estimate the effects of the wildfire-related smoke on changes in ground-level PM2.5. We then estimate the relationship between smoke-induced air pollution and credit outcomes using a panel data model with two-way fixed effects. Exposure to heavy pollution resulted in an increase in mortgage, credit card, and retail/store card delinquencies. Households living in zip codes with high levels of pollution from the Camp Fire, for example, also demonstrated extra credit card spending and less credit card repayment. Estimated effects of wildfire-induced pollution on household credit usage and credit performance are smaller than those from wildfire structural damage, however, smoke-affected population is substantially diffused among much larger geography.

Overall, findings indicate that adverse effects of wildfires can go far beyond the fire perimeter. In the case of wildfire-induced particulate pollution, the estimated increase in household financial distress is salient to large numbers of households living beyond the fire perimeter. Failure to account for broadly diffused and consequential smoke and pollution events yields a partial and incomplete rendering of household financial effects of extreme wildfires. Finally, future research should assess the external validity of findings to virulent wildfire and related smoke and pollution events increasingly evidenced in such places as eastern Canada and southern Europe.

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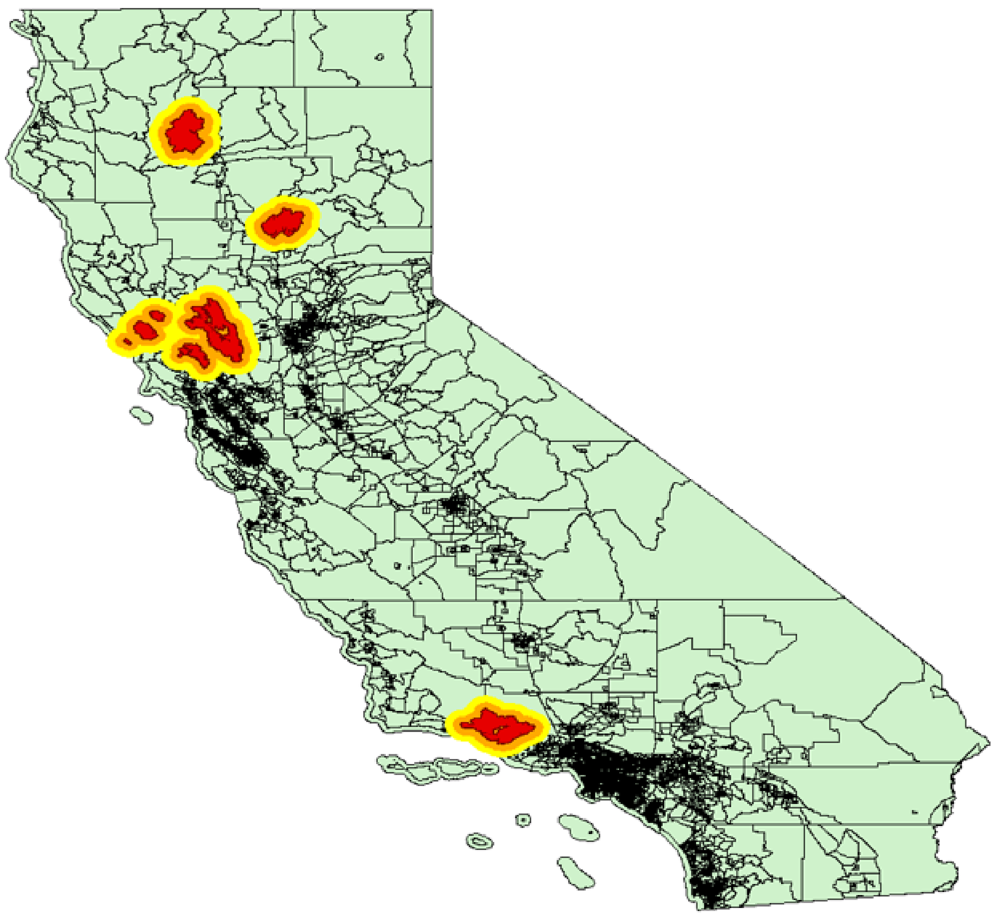


Figure 1. Extreme Wildfires in CA between 2016-2020 and the 1-, 5-, and 10- mile Peripheral Rings

Notes: This figure shows the geographic location of the extreme wildfires (with more than 1,000 destroyed structures) in California between 2016-2020. The red area is the fire footprint; the brown, orange, and yellow areas are the 1-mile, 5-mile, and 10-mile peripheral rings, respectively.

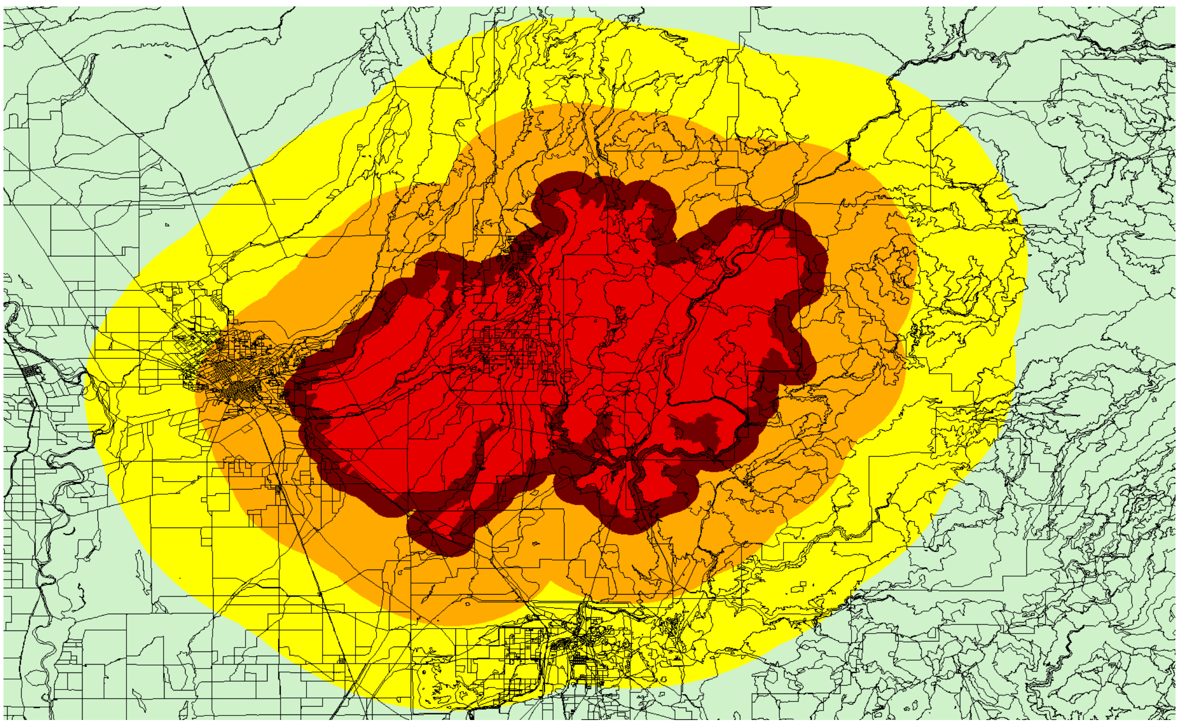


Figure 2. Treatment and Control Areas in the Camp Fire Analyses

Notes: This figure shows the treatment and control areas in the Camp fire analyses. The red area is the fire footprint, which is the treatment area; the brown area is a 1-mile peripheral ring, which we carve out in our analysis; the orange area is a 1- to 5-mile peripheral ring, which is the control area; and the yellow area is a 5- to 10-mile peripheral ring, which is an alternative control area. The border lines are census blocks in California.

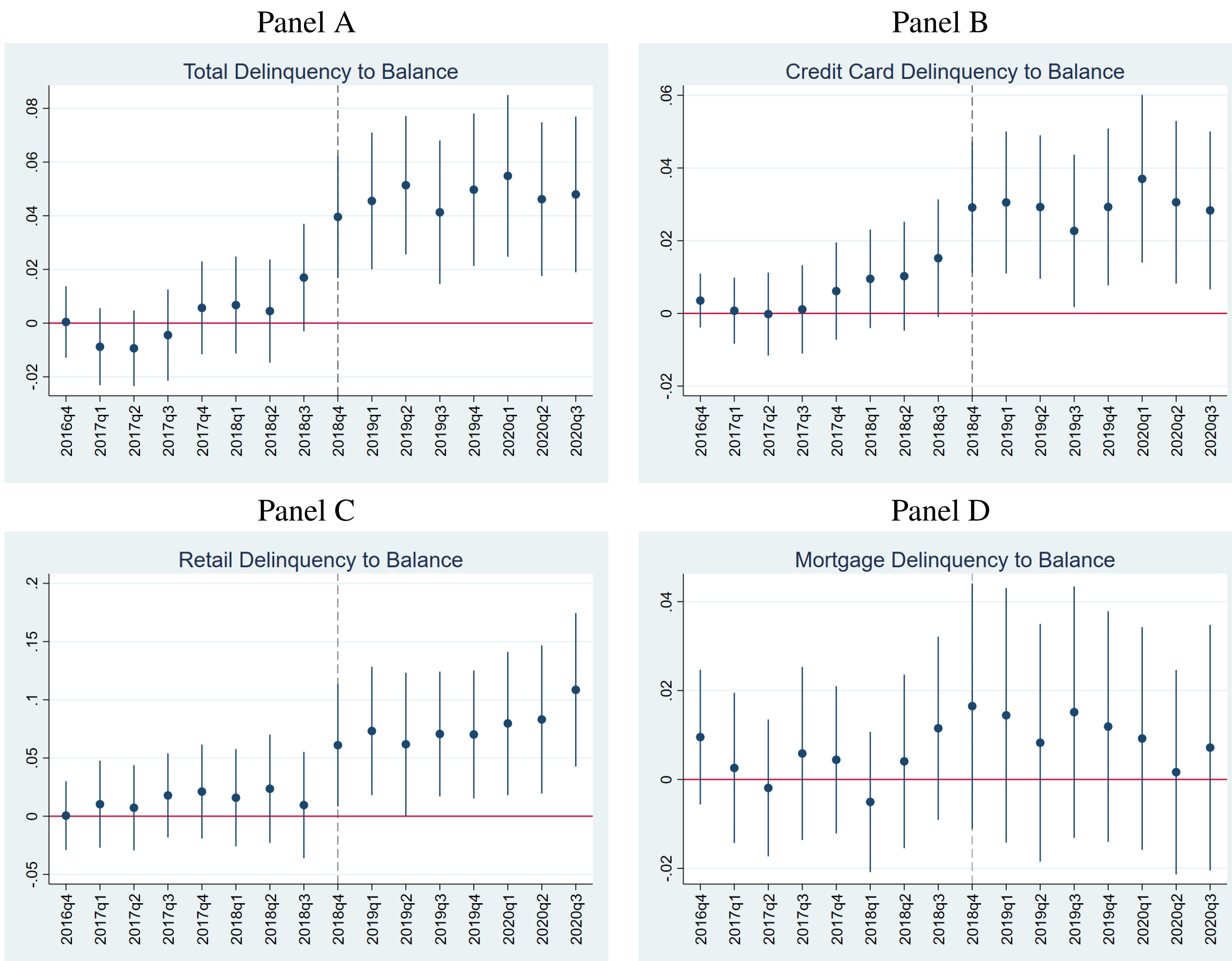
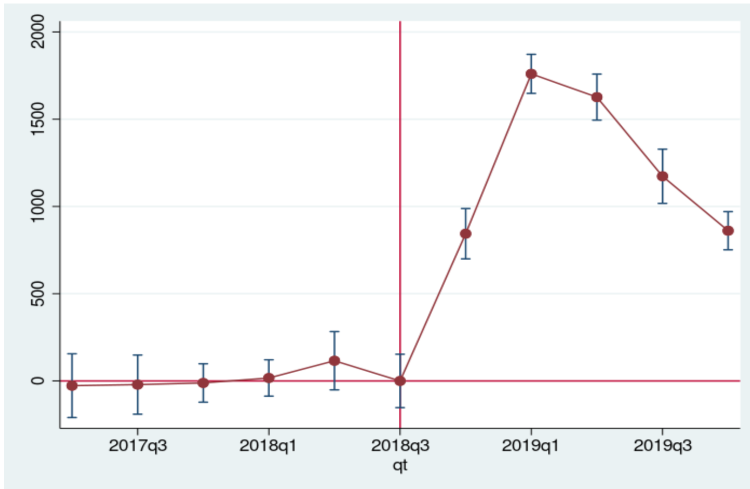
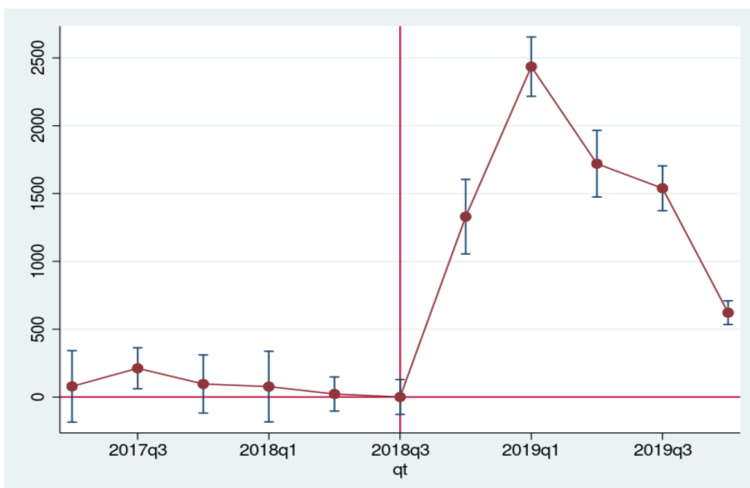


Figure 3. The Effect of the Camp Fire on Household Financial Distress

Notes: This figure shows the temporal pattern of the estimated Camp fire effect on consumer credit delinquency rates in a difference-in-differences framework. We compare consumers living in wildfire-burned areas (the treatment group) with those that are 1-5 miles away from the fire perimeter (the control group), before and after the Camp Fire. Control variables include borrowers' characteristics (age and Equifax Risk Score), location, and time-fixed. Data sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.



Panel A Credit card spending



Panel B Credit card repayment

Figure 4. Effects of the Camp Fire on Credit Card Spending and Repayment

Notes: This figure shows the temporal pattern of the estimated Camp fire effect on credit card spending and repayment in a difference-in-differences framework. We compare borrowers living in wildfire burn areas (the treatment group) with those that are 1-5 miles away from the fire perimeter (the control group), before and after the Camp Fire. We include account fixed effects and year-month fixed effects. Additional time-varying control variables include refreshed borrower credit score and current credit limit of the credit card account. Data Sources: air pollution data are from from the EPA's Air Quality System, and credit card data are from the Federal Reserve Y-14M.

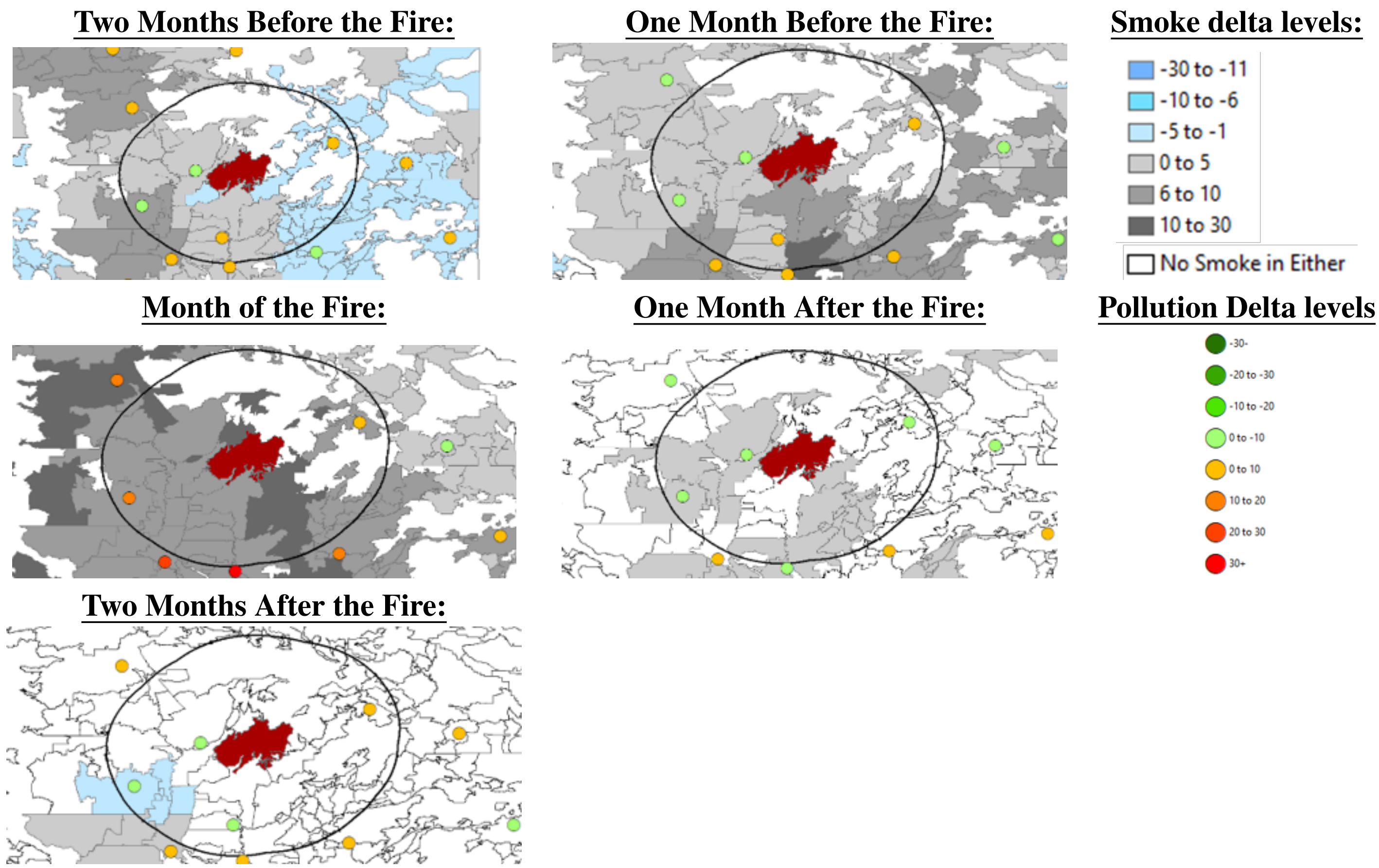
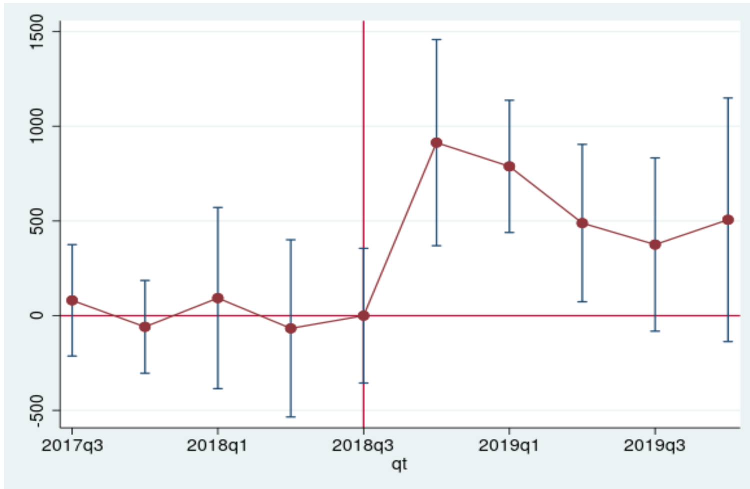
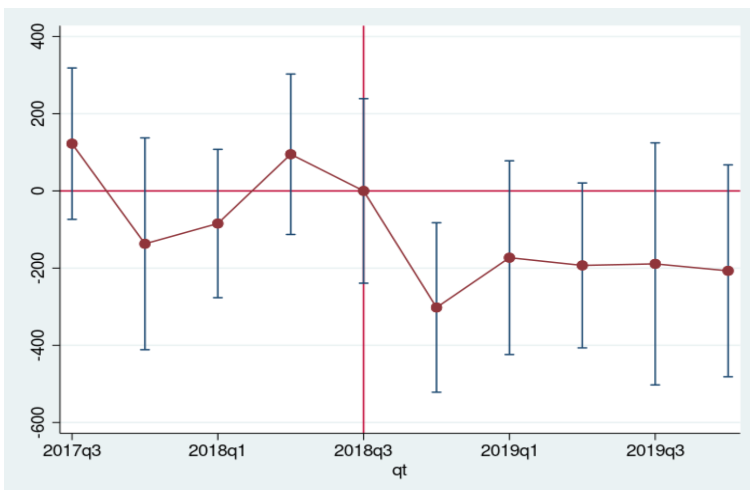


Figure 5. Delta Smoke and Pollution – Camp Fire

Notes: This figure shows the variation in changes in smoke and pollution (relative to the same months in 2015) two months before and after the Camp Fire. 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 relative to the same month in 2015 (the base year). The dots represent the pollution monitors, where shades of green represent a decline in pollution levels compared with the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared with the same month in 2015.



Panel A Credit card spending



Panel B Credit card repayment

Figure 6. Effects of Camp Fire-Induced Air Pollution on Credit Card Spending and Repayment
Notes: This figure shows the temporal pattern of the estimated effect of Camp fire-induced air pollution on credit card spending and repayment in a difference-in-differences framework. We focus on areas that are 5-30 miles away from the Camp fire perimeter (to isolate smoke effect from direct fire effect) and compare borrowers that were exposed to heavy pollution (pollution level above the 75 percentile) to those exposed to light pollution (pollution level in the bottom quartile), before and after the Camp Fire. We include account fixed effects and year-month fixed effects. Additional time-varying control variables include refreshed borrower credit score and current credit limit of the credit card account. Data Sources: air pollution data are from from the EPA's Air Quality System, and credit card data are from the Federal Reserve Y-14M.

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. Effects of Camp Fire on Net Migration

	1	2	3	4	5
	Move-in	Move-out		Net migration	
Treated × *Post* 0 vs 5 miles	1.97	19.2***	17.7***		
	(2.87)	(1.92)	(5.27)		
Treated×*Post* 0 vs 10 miles				9.28***	
				(2.23)	
Treated×*Post* 0 vs 20 miles					3.2***
					(1.29)
Census tract FE	+	+	+	+	+
Year-qtr FE	+	+	+	+	+
Observations	470	470	470	674	1,023
R-squared	0.49	0.47	0.15	0.11	0.10
Dependent variable mean	36.02	33.18	6.96	2.31	2.67

Notes: This table shows the results of the estimation of the effect of the Camp Fire on migration. We compare wildfire-treated tracts (e.g., tracts within the burn footprint) to control tracts, before and after the event. The time frame is two years before and after each fire. All columns include time and location fixes effect. The first three columns show the results of the estimation of the effect of the Camp Fire on in-migration, out-migration, and net-migration. Net migration is defined as the out-migration minus in migration as a percentage of the population in the census tract. Column 4 compares net-migration between the fire zone to tracts that are from 1 - 10 miles from the fire, and column 5 compares tracts in the fire zone to those 1 - 20 miles from the 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 3. Effects of the Camp Fire on House Prices

	1 House Price Index	2 Number of Transactions	3 Repeated Sales Median Price	4 Residential Vacancy Rate
Treated×Post	-17.54***	-4.22***	-34,553.88***	0.08***
	(0.93)	(1.84)	(4,937.23)	(0.01)
Census tract FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	475	475	475	353
R-squared	0.84	0.80	0.75	0.56
Dependent variable mean	244.4	20.6	280,007	0.03

Notes: This table shows the results of difference-in-differences estimation of the effect of the 2018 Camp Fire on house prices and vacancy rate for census tracts in the fire zone vs. census tracts 1 to 5 miles farther from the Camp Fire perimeter. Column 1 reports the effect of Camp Fire on the home price index, column 2 reports the effect on number of sales transactions, column 3 on repeat median sales price, and column 4 on residential vacancy rate. All estimations include time and location fixed effect. The time frame is two years before and after each fire. Standard errors clustered by census blocks in parentheses: ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: CoreLogic Home Price Index (HPI) and U.S. Department of Housing and Urban Development.

Table 4. Effects of the Camp Fire on Consumer Financial Distress

	1 Mortgage Delinquency	2 Credit Card Delinquency	3 Personal Loan Delinquency	4 Retail/Store Card Delinquency
Treated×Post	0.02*	0.02***	0.05*	0.02
	(0.01)	(0.01)	(0.03)	(0.02)
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	20,686	71,964	11,544	17,282
R-squared	0.54	0.77	0.74	0.73
Dependent variable mean	0.01	0.04	0.08	0.12

Notes: This table shows the results of the estimation of the effect of the Camp fire on delinquency rates. We compare consumers residing in wildfire-treated census blocks (e.g., blocks within the burn footprint) to those residing in control blocks up to 1-5 miles from the fire, before and after the fire. All specifications include consumer 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. 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 5. Effects of the Camp Fire on Credit Card Spending and Repayment

	1 Δ Spending	2 Δ Payment	3 Δ Balance	4 Δ Past Due
Treated × *Post*	1112.313***	1557.085***	-1889.632***	0.043***
	(96.845)	(99.488)	(194.097)	(0.006)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
Observations	1,084,138	1,084,138	1,084,138	1,084,138
R-squared	0.064	0.039	0.261	0.255
Dependent variable mean	-67.483	349.869	464.118	0.095

Notes: This table shows the difference-in-differences estimates of the effect of wildfire on credit card spending, repayment, balance, and past due. We compare borrowers residing in wildfire burn areas to those residing between 1 to 5 miles from the fire perimeter, before and after the Camp Fire. The time frame is 14 months before and after the Camp Fire. Year-over-year change (Δ) in spending, payment, and balance are annualized dollar amounts. Time-varying borrower attributes include updated borrower credit score and current credit limit of the credit card account. Robust standard errors in parentheses (error terms clustered at the zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Data Sources: US Department of Homeland Security National Incident Management System/Incident Command System (ICS) and Monitoring Trends in Burn Severity (MTBS) databases; Federal Reserve Y-14M for credit card data.

Table 6. Heterogeneous Effects of Camp Fire on Credit Card Balance and Delinquency

	Homeowners		Renters	
	1	2	3	4
Panel A: Credit Balance	Credit Score ≤ 720	Credit Score > 720	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	-3,195.09	-1,404.54*	-866.16	108.21
	(3,797.26)	(745.91)	(995.98)	(436.06)
Time-varying borrower attributes	✓	✓	✓	✓
Census tract FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	691	4,505	6,282	6,282
R-squared	0.37	0.37	0.22	0.15
Dependent variable mean	7,382.2	3,674.5	3,125.1	2,114.1
Panel B: Delinquency	Credit Score ≤ 720	Credit Score > 720	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	0.00	0.00	0.06***	0.00
	(0.01)	(0.00)	(0.02)	(0.00)
Time-varying borrower attributes	✓	✓	✓	✓
Census tract FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	3,376	17,319	28,297	22,964
R-squared	0.14	0.04	0.14	0.04
Dependent variable mean	0.01	0.00	0.11	0.00

Notes: This table shows the effect of the Camp fire on credit card balance and delinquency, in Panel A and Panel B respectively, based on subsamples for different credit score segments. We compare consumers residing in wildfire-treated census blocks (e.g., blocks within the burn footprint) to those residing in control blocks up to 1-5 miles from the fire, before and after the fires. The time frame is two years before and after the Camp fire. 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. Homeowners define as those with a positive amount of mortgage balance. 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. Effects of Camp Fire-Induced Pollution on Credit Outcomes

Panel A	1 Mortgage Delinquency	2 Credit Card Delinquency	3 Personal Loan Delinquency	4 Retail/Store Card Delinquency
$Treated \times Post$	0.01***	0.02***	0.05**	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Time-varying borrower attributes	✓	✓	✓	✓
Borrower FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	5,846	20,730	3,023	5,007
R-squared	0.31	0.78	0.76	0.79
Dependent variable	0.01	0.04	0.13	0.10
Panel B	Mortgage Delinquency	Credit Card Delinquency	Personal Loan Delinquency	Retail/Store Card Delinquency
$Treated \times Post$	0.01	0.02*	0.01	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Time-varying borrower attributes	✓	✓	✓	✓
Borrower FE	+	+	+	+
Q-year FE	+	+	+	+
Observations	3,892	5,893	6,035	5,861
R-squared	0.59	0.71	0.72	0.72
Dependent variable	0.02	0.04	0.11	0.11

Notes: This table shows the OLS and IV estimates, in Panel A and Panel B respectively, of the effect of wildfire-related air pollution on credit delinquencies. We compare wildfire-treated ZIP Codes that were exposed to pollution levels above the 75 percentile, to those with lower pollution levels, below the 25 percentile, before and after the Camp Fire. We focus on zipcodes located 5 to 30 miles from the Campfire. The time frame is two years before the Camp Fire and 18 months after. Robust standard errors in parentheses (error terms clustered at zipcode-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Air pollution data were obtained from the EPA's Air Quality System, and Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Table 8. Effects of Camp Fire-Induced Pollution on Credit Card Spending and Repayment

Panel A	1 Δ Spending	2 Δ Payment	3 Δ Balance	4 Δ Past Due
Treated × *Post*	389.056***	-173.050***	502.849***	0.022***
	(62.530)	(40.885)	(103.710)	(0.001)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Month-year FE	+	+	+	+
Observations	712,567	712,567	712,567	712,567
R-squared	0.079	0.052	0.257	0.092
Dependent variable mean	-391.821	435.421	1,160.981	0.116
Panel B: IV	Δ Spending	Δ Payment	Δ Balance	Δ Past Due
Treated × *Post*	383.133***	-167.930***	525.183***	0.021***
	(61.975)	(38.180)	(118.780)	(0.001)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month	+	+	+	+
Observations	701,778	701,778	701,778	701,778
R-squared	0.078	0.050	0.258	0.093
Dependent variable mean	-398.244	428.649	1188.219	0.117

Notes: This table shows the OLS and IV estimates, in Panel A and Panel B respectively, of the effect of wildfire-related air pollution on credit card spending, payment, balance, and past due in a difference-in-differences framework. We focus on areas that are 5-30 miles away from the Camp fire perimeter (to isolate smoke effect from direct fire effect) and compare borrowers that were in zip codes exposed to heavy pollution (pollution level above the 75 percentile) to those in zip codes exposed to light pollution (pollution level in the bottom quartile), before and after the Camp fire. The time frame is 14 months before and after the Camp fire. Year-over-year change (Δ) in spending and payment are annualized dollar amounts. We include account fixed effects and year-month fixed effects. Additional time-varying control variables include refreshed borrower credit score and current credit limit of the credit card account. Robust standard errors in parentheses (error terms clustered at the zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Data Sources: EPA's Air Quality System for air pollution data; Federal Reserve Y-14M for credit card data.

Table 9. Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Payment: Different Credit Score Segments

	1	2
Panel A: Δ Spending	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	140.061	535.442***
	(107.843)	(88.154)
Time-varying borrower attributes	✓	✓
Account FE	+	+
Year-month FE	+	+
Observations	249,317	449,846
R-squared	0.131	0.076
Dependent variable mean	-1,048.704	-36.189
Panel B: Δ Payment	Credit Score ≤ 720	Credit Score > 720
$Treated \times Post$	-445.491***	-26.773
	(89.364)	(70.242)
Time-varying borrower attributes	✓	✓
Account FE	+	+
Year-Month FE	+	+
Observations	249,317	449,846
R-squared	0.093	0.052
Dependent variable mean	489.834	394.592

Notes: This table shows the IV estimates of the effect of wildfire-related air pollution on credit card spending and payment, in Panel A and Panel B respectively, based on subsamples for different credit score segments. We compare borrowers in wildfire-treated Zip Codes that were exposed to high pollution levels (those in the upper quartile), to those in Zip codes exposed to lower pollution levels (those in the bottom quartile), before and after the Camp Fire. The time frame is two years before and after the Camp wildfire. Year-over-year change (Δ) in spending and payment are annualized dollar amounts. Time-varying borrower attributes include current credit score (40-point) bins and current credit limit bins. Robust standard errors in parentheses (error terms clustered at the zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Data Sources: EPA's Air Quality System for air pollution data; Federal Reserve Y-14M for credit card data.

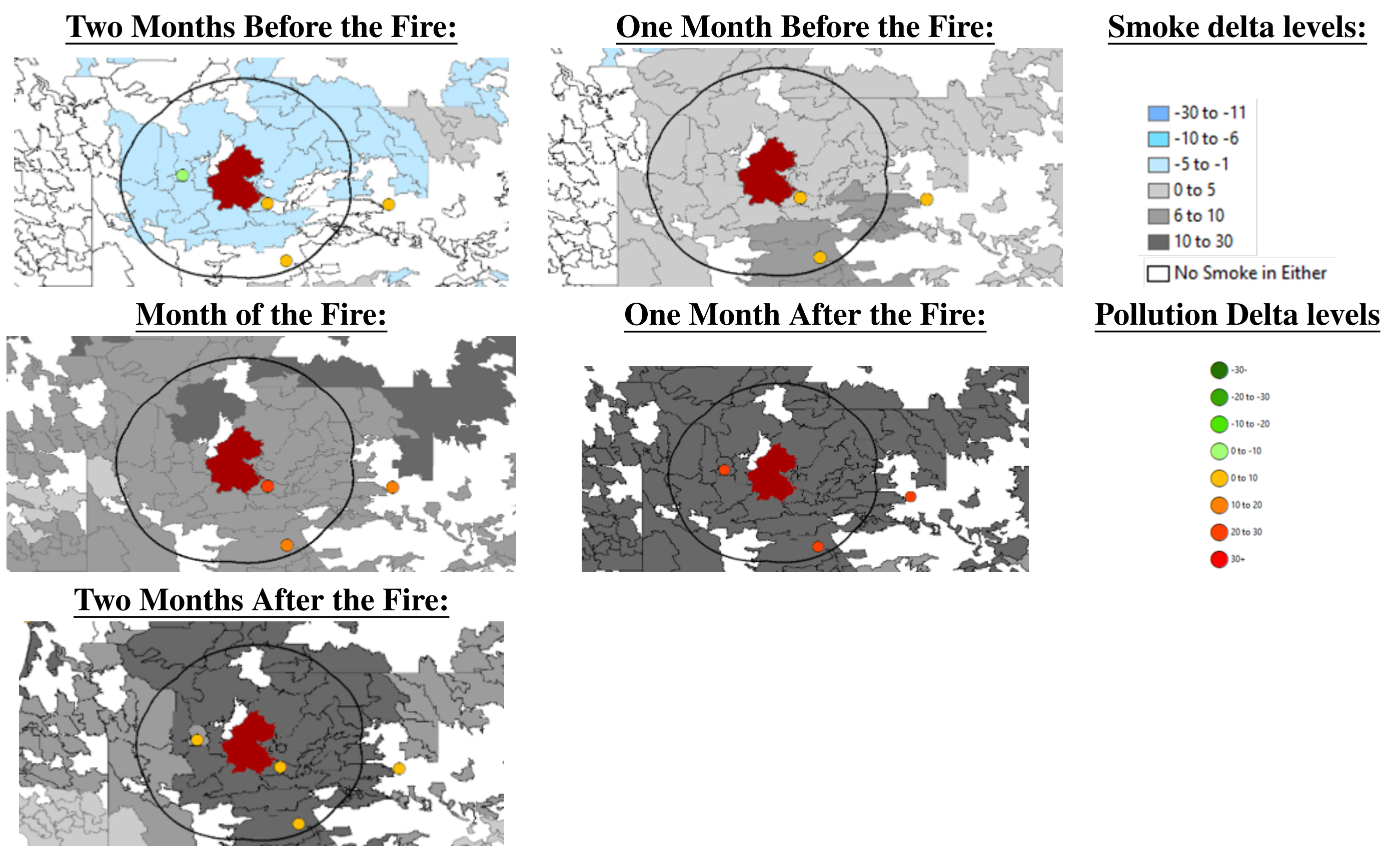


Figure A.1. Delta Smoke and Pollution - Carr Fire

Notes: This figure shows the variation in changes in smoke and pollution (relative 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 relative to the same month in 2015 (the base year). The dots represent the pollution monitors, with green shades representing a decline in pollution levels relative to the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels relative to the same month in 2015.

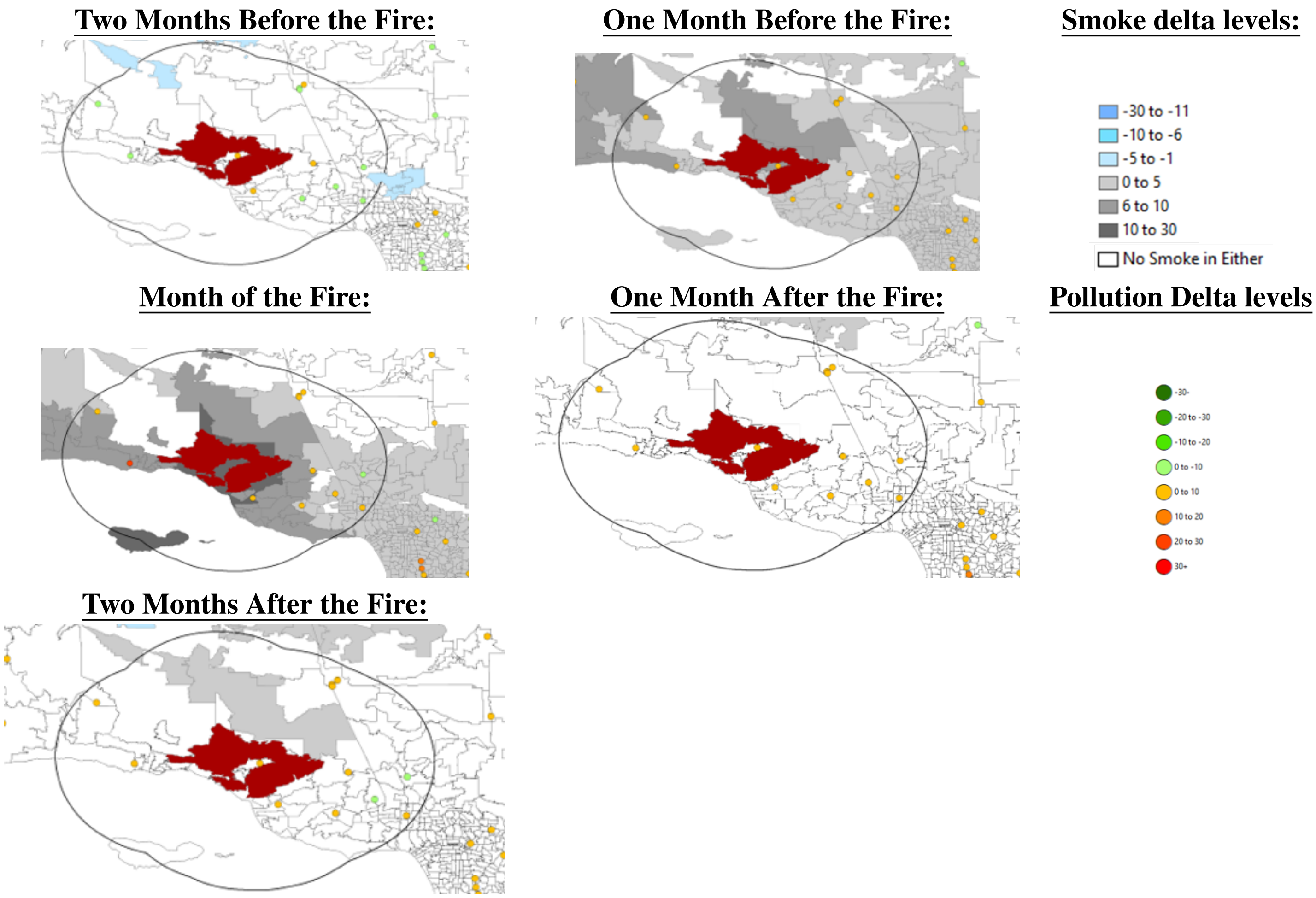


Figure A.2. Delta Smoke and Pollution - Thomas Fire

Notes: This figure shows the variation in changes in smoke and pollution (relative 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 relative 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 Relaive to the same month in 2015 (the base year). The orange-red color of the pollution monitors means an increase in pollution levels compared with the same month in 2015.

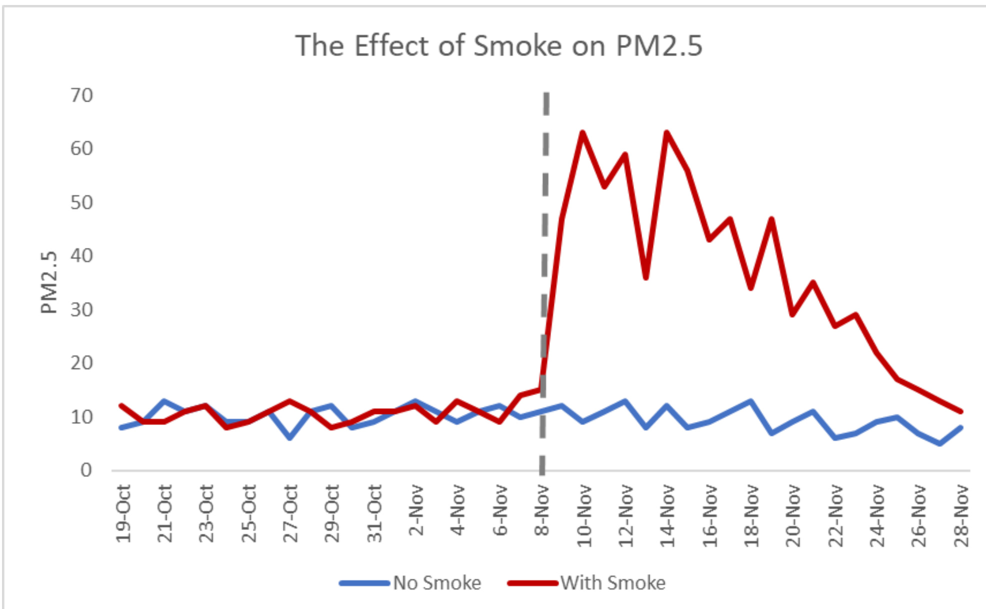


Figure A.3. Wildfire Smoke Elevated PM2.5 After the Camp Fire

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.4. 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 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. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

Figure A.5. The Effect of 2018 Camp Fire on the Number of Accounts and Credit Balance - from the FRBNY Consumer Credit Panel/Equifax Data

Notes: This figure shows the time dynamic of estimated Camp Fire-related number of mortgage account, number of bank credit card accounts, mortgage balance, and credit card balance 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 changes in balance restricted to households that experienced no change in the number of accounts. The figure shows the time dynamic patterns a few quarters prior and subsequent to the Camp Fire event, occurred in California during November 2018. Sources: Federal Reserve Bank of New York/Equifax Consumer Credit Panel.

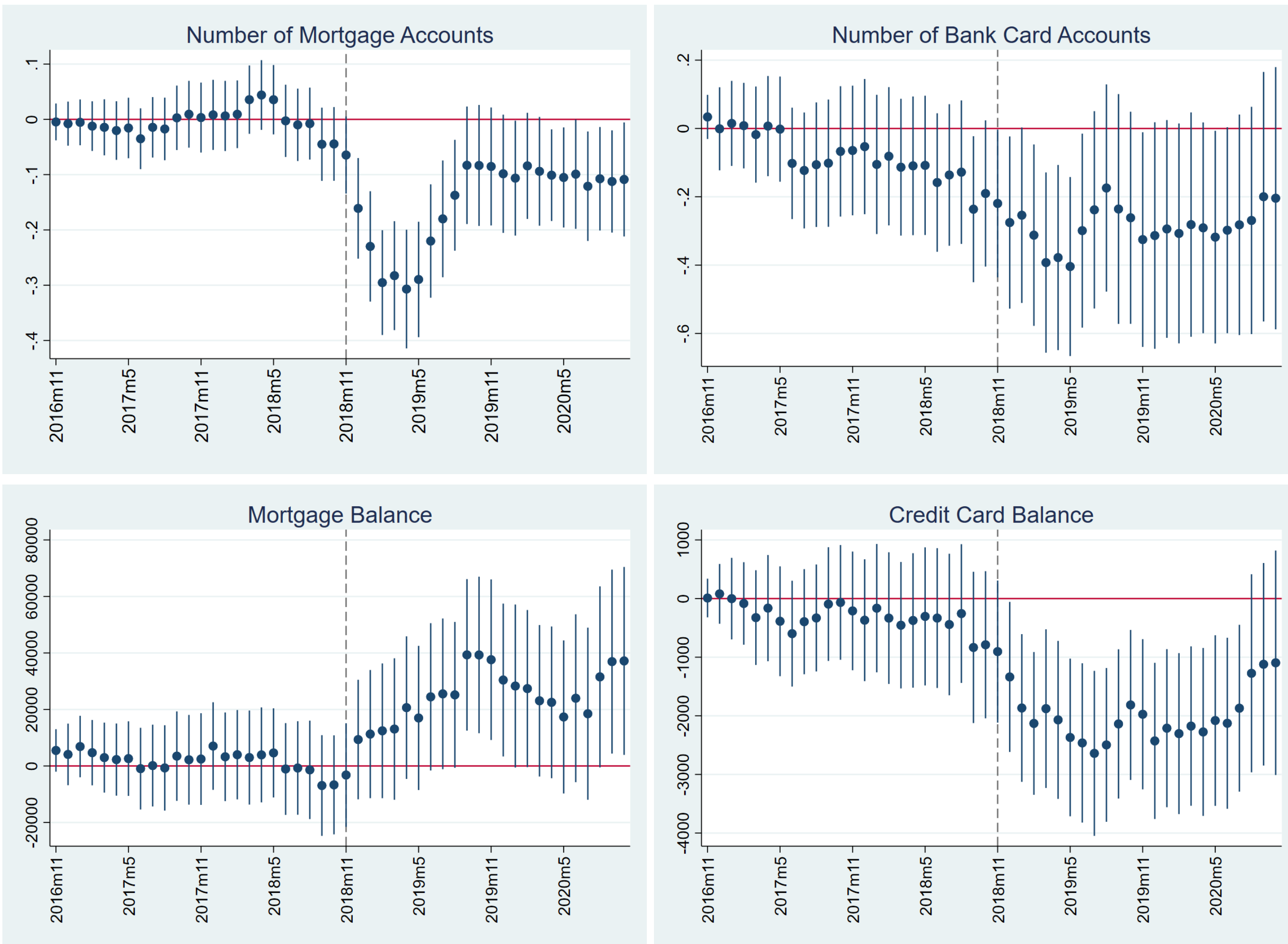


Figure A.6. The Effect of 2018 Camp Fire on Credit Balance and Number of Accounts - From the CRISM

Notes: This figure shows the time dynamic of estimated Camp Fire-related credit balance and number of credit accounts, 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 changes in balance restricted to households that experienced no change in the number of accounts. The figure shows the time dynamic patterns from the CRISM, 24 months prior and subsequent to the Camp Fire event, occurred in California during November 2018. Sources: Equifax CRISM dataset.

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 . 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 Delinquency Rate	15,249	0.04	0.17	84,248	0.04	0.17
Personal Loan Delinquency Rate	2,511	0.07	0.25	14,459	0.08	0.26
First Mortgage Delinquency 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
Equifax Risk 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 fire zone (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 (Camp, Carr, Thomas, Central LNU Complex, and LNU Lightning Complex). Source: Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP).

Table A.3 . Heterogeneous Effects of Extreme Wildfires on Financial Distress: Different Fires

	1	2	3	4	5	6
	CARR		Thomas		central LNU complex	
	Bank card Delinquency	Mortgage Delinquency	Bank card Delinquency	Mortgage Delinquency	Bank card Delinquency	Mortgage Delinquency
Treated	-0.00	-0.04*	-0.00	-0.01	0.01	0.03**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Treated $\times$ *Post*	0.00	0.02	-0.01	0.02*	-0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Time-varying borrower attributes	✓	✓	✓	✓	✓	✓
Census tract FE	+	+	+	+	+	+
Year-qtr FE	+	+	+	+	+	+
Observations	57,087	19,398	126,403	7,257	89,411	1,297
R-squared	0.14	0.16	0.14	0.23	0.14	0.19
Dependent variable	0.04	0.02	0.03	0.02	0.03	0.02

Notes: This table shows the results of the estimation of the effect of Carr, Thomas, and LNU fires on delinquency rates. We compare consumers residing in wildfire-treated census blocks (e.g., blocks within the burn footprint) to those residing in control blocks up to 1-5 miles from the fire, before and after the fires. All specifications include borrowers' characteristics (age and Equifax risk score), location, and time-fixed effects. The analysis includes eight quarters prior to and eight 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 Equifax risk score. 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 A.4 . Effects of Extreme Wildfires on the Number of Credit Accounts

	1	2	3	4	5	6	7	8
	Camp Fire		Thomas Fire		Carr Fire		LNU complex	
	Bank Card Number Accounts	First Mortgage Number	Bank Card Number Accounts	First Mortgage Number	Bank Card Number Accounts	First Mortgage Number	Bank Card Number Accounts	First Mortgage Number
Treated	0.25	0.033	-0.04	-0.03	0.34	0.19**	0.07	0.13*
	(0.27)	(0.06)	(0.19)	(0.07)	(0.23)	(0.09)	(0.27)	(0.08)
$Treated \times Post$	-0.37***	-0.12***	-0.09*	-0.00	-0.29***	-0.02	-0.15*	-0.01
	(0.07)	(0.02)	(0.05)	(0.02)	(0.11)	(0.03)	(0.08)	(0.02)
Borrowers Characteristics	✓	✓	✓	✓	✓	✓	✓	✓
censustract fe	+	+	+	+	+	+	+	+
Year-Month fe	+	+	+	+	+	+	+	+
Observations	87,367	87,367	149,839	149,839	68,183	68,183	122,107	122,107
R-squared	0.04	0.12	0.03	0.11	0.03	0.10	0.03	0.16
Dependent variable	1.85	0.28	2.12	0.33	1.94	0.32	2.27	0.37

Notes: This table shows the results of estimation of the effect of extreme fires on the number of accounts. We compare consumers residing in wildfire-treated census blocks (e.g., blocks within the burn footprint) to those residing in control blocks up to 1-5 miles from the fire, before and after the fires. WWe 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. All specifications include borrowers' characteristics (age and Equifax Risk Score), location, and time-fixed effects. The analysis includes 24 months prior and subsequent to the Camp Fire event, occurred in California during November 2018. 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 A.5 . Summary Statistics for Smoke and Pollution

	1	2	3	4	5	6	7	8	9	10	11	12
After the event	Camp Fire			Carr Fire			Thomas Fire			Central LNU Complex		
	Obs	Mean	S.d.	Obs	Mean	S.d.	Obs	Mean	S.d.	Obs	Mean	S.d.
smoke_days	151,229	5.3	8.2	106,214	3.8	6.0	353,926	0.2	0.4	183,419	4.3	5.3
smoke_delta	151,229	1.3	4.7	106,214	1.1	3.4	353,926	-3.0	3.2	183,419	-0.3	7.0
pm25	151,229	12.4	13.7	106,214	6.1	3.0	353,926	6.8	2.6	183,419	7.7	3.4
pm25_delta	151,229	3.7	13.1	106,214	0.9	3.1	353,926	-2.6	1.8	183,419	0.0	2.8

Notes: This table provides summary statistics for smoke days, pollution levels (pm2.5), and the change in smoke days and pollution levels compared with 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 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).

Table A.6 . Effects of Wildfire 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	0.38***		0.05	1.15***			2.44***	1.25***		
	(0.12)		(0.05)	(0.04)			(0.33)	(0.13)		
smoke_delta		0.54***			0.07	1.85***			2.09***	0.91***
		(0.14)			(0.16)	(0.15)			(0.39)	(0.12)
zipcode fe	+	+	+	+	+	+	+	+	+	+
Year-Month 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	0.38	0.39	0.96	0.63	0.95	0.61	0.79	0.55	0.77	0.49

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 A.7 . Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Repayment: Different Fires

Panel A: Δ Spending	1 Camp Fire	2 Thomas Fire	3 CARR Fire	4 Central LNU
$Treated \times Post$	383.133***	398.239	863.962***	141.364
	(61.975)	(576.381)	(396.155)	(294.493)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Month-year FE	+	+	+	+
Observations	701,778	160,516	92,115	381,834
R-squared	0.078	0.100	0.053	0.045
Dependent variable mean	-398.244	-347.286	-245.364	-296.653
Panel B: Δ Payment	Camp Fire	Thomas Fire	CARR Fire	Central LNU
$Treated \times Post$	-167.930***	-280.467	-1636.310***	-258.522
	(38.180)	(406.342)	(118.780)	(292.491)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month FE	+	+	+	+
Observations	701,778	160,516	92,115	381,834
R-squared	0.050	0.051	0.022	0.027
Dependent variable mean	428.649	72.140	124.304	132.852

Notes: This table shows the IV estimates of the heterogeneous effects of air pollution attributed to different wildfires on credit card spending and payment, in Panel A and Panel B respectively. We focus on areas that are 5-30 miles away from the wildfire perimeter (to isolate smoke effect from direct fire effect) and compare borrower in zip codes that were exposed to heavy pollution (pollution level above the 75 percentile) to those in zip codes exposed to light pollution (pollution level in the bottom quartile), before and after the wildfire. The time frame is one to two years before and after each wildfire, depending on specific wildfire. Year-over-year change (Δ) in spending and payment are annualized dollar amounts. We include account fixed effects and year-month fixed effects. Additional time-varying control variables include refreshed borrower credit score and current credit limit of the credit card account. Robust standard errors in parentheses (error terms clustered at the zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Data Sources: EPA's Air Quality System for air pollution data; Federal Reserve Y-14M for credit card data.