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 wildfire smoke and related air pollution events on household financial outcomes. We find increased spending, indebtedness, and loan delinquencies among households distant from the burn perimeter but exposed to high levels of wildfire-attributed air pollution. Further analysis points to a health-related spending channel in explanation of the adverse financial effects. The estimated effects of wildfire smoke and pollution are salient to a substantial geographically dispersed population and add appreciably to estimates of household financial distress in the wake of these extreme climatic events.

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I. Introduction

Recent decades have witnessed more frequent and more extreme wildfire events. U.S. wildfires on average were four times in size, triple in frequency, and more widespread during the 2000s than in prior decades (Iglesias et al., 2022). Further, adverse environmental impacts of wildfires often extend well beyond the burn perimeter: In 2020, smoke from wildfires, on average, covered U.S. and California counties for 20 and 64 days, respectively. More recently, in the wake of 500 active wildfire events in eastern Canada in June 2023, 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. An emerging literature has sought to document economic effects of climate shocks on proximate housing and household finance (see, for example, Bernstein et al. (2019) and Keys and Mulder (2020)), Yet there has been only limited attention to household financial distress in the wake of extreme wildfire and dispersed smoke and pollution events. Those outcomes likely are salient to large populations well beyond the fire zone.

Wildfire smoke has emerged as the primary source of air pollution (Burke et al., 2021). Recent literature has documented the adverse effects of smoke-related pollution on health (Deryugina et al., 2019), medical spending, labor market, and other outcomes (see Aguilar-Gomez et al. (2022) for a review). For example, wildfire smoke and related spikes in particulate emissions may result both in increased medical expenses and in demand for goods and services that mitigate deleterious air pollution health effects (notably including increased medical and medical equipment spending). Smoke events also have been shown to result in work interruption and in reductions to earnings (Borgschulte et al. (2022)) and business activity in tourism and outdoor recreation (Stotts et al., 2018). Together, these studies suggest potential declines in health, loss of income, and deterioration in household financial status in the aftermath of an extreme smoke event.

In this paper, we provide novel estimates of the effects of distant wildfire-attributed smoke and particulate emissions on consumer financial and health outcomes. The paper is among the first to explore the effects of smoke and pollution events among large populations and geographies well beyond the fire zone. To complement the above analysis, we also provide estimates of proximate within burn perimeter household financial effects of those same extreme wildfires. The addition of distant smoke and pollution to localized burn effects adds much to our understanding of adverse financial impacts of extreme wildfire events.

Our analysis is based on the unique combination of specialized and highly-articulated datasets on wildfire-induced smoke plumes, attributable and localized air pollution, wildfire zone structural damage, and related household financial, economic, and health outcomes. The U.S. National Incident Command System Incident Status Summary Forms provide information on the geographic incidence of wildfire structural damage (St Denis et al., 2020). As shown in Appendix Table A.1 , the large majority of extreme wildfires 2016-2020 occurred in California. Our analysis focuses on smoke and pollution effects associated with the 2018 Camp Fire, far and away the most damaging of U.S. wildfires to date. We compare results of the Camp Fire to a geographically diverse sample of California extreme wildfires. We use daily ground monitor readings for Environmental Protection Agency (EPA) "criteria pollutants," including a metric of particulate matter ($PM_{2.5}$), to measure ground-level pollution and to estimate the increment in pollution owing to wildfire smoke. In that measured $PM_{2.5}$ could reflect changes in pollution levels due to factors other than wildfire smoke, we also estimate household financial effects using results of a machine learning model developed by Childs et al. (2022) on wildfire smoke contributions to daily $PM_{2.5}$ concentration over a 10 km-by-10 km grid across the contiguous US. We employ detailed consumer-level and loan-level datasets, including the FRBNY Consumer Credit Panel/Equifax Data (CCP); the Equifax Credit Risk Servicing McDash (CRISM);[1] and the Federal Reserve Y-14M Capital As-

[1] CRISM is a match between anonymous credit reports from Equifax and administrative mortgage data from Black Knight McDash.

sessments and Stress Testing Data to measure consumer credit outcomes. Data on health outcomes is obtained from the California Health and Human Services Open Data Portal. The combination of comprehensive and granular wildfire, wildfire-smoke pollution, and consumer health and financial data provides unparalleled and unique opportunities to identify the causal impacts of proximate wildfire and dispersed wildfire-attributable air pollution on household financial outcomes.

Our research design enables us to separate proximate wildfire from more distant wildfire-attributable smoke and air pollution effects. In the burn zone, households are affected both by fire damage and by related smoke and pollution. To distinguish wildfire smoke and pollution from burn zone effects, we carve out the wildfire burn area and its immediate perimeter, and focus on areas 5-30 miles from the wildfire boundary. Those areas are typically not directly damaged by the wildfire but often are affected by wildfire smoke. Due in part to topology and wind direction, in the wake of an extreme wildfire event, some of those more distant areas may be covered by heavy smoke while others might experience only light smoke. We thus leverage smoke and pollution variations in our identification strategy. Specifically, we compare distant households in zip codes exposed to heavy pollution to those in zip codes exposed to light pollution, before and after the wildfire, in a difference-in-differences (DID) framework. In an effort to ensure 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 $PM_{2.5}$ levels and same month $PM_{2.5}$ levels in the prior year. Second, we estimate the effects of particulate emissions using an instrumental variable approach. Given the granularity of our data, we are able to include consumer- or credit account-level fixed effects, so as to largely alleviate concerns of omitted variable bias. To assess direct fire treatment effects for households in wildfire burn zones, we use a similar DID framework to compare credit usage and credit performance within the burn perimeter (the treatment group) to those same outcomes in 1- and 5-mile rings beyond the wildfire zone (the control group).

Our results provide new evidence of adverse causal impacts of distant wildfire-induced air pollution on credit outcomes. We find statistically significant and economically salient increases in loan delinquency (including credit card, personal loan, and retail card delinquency) in the wake of a fire-attributable pollution event. Using highly articulated individual account-level Y-14M consumer credit data, we show that those same wildfire-related pollution events are associated not only with increases in credit card past due, but also with higher levels of credit card spending and declines in credit card payments. In the five quarters following the Camp Fire, for example, the combination of additional credit card spending and reduced credit card repayment among consumers exposed to high levels of wildfire-induced particulate pollution added about $1,400 per annum to credit card balance. Further analysis indicates 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 emergency government assistance, typically have fewer resources to cope with labor market or health effects of major pollution events. By contrast, the increase in credit card spending is found largely among prime borrowers, who likely have the capacity to spend more on preventive measures to combat wildfire-induced air pollution. In an effort to better understand the spending mechanism, we turn to health outcomes and find significant adverse effect of the smoke and pollution events on child and adult respiratory disease emergency department visits. Those findings point to a health-related spending channel in explanation of the adverse wildfire smoke and pollution financial effects.

As a comparison, we also estimate direct burn zone impacts of wildfire. Here we contrast financial outcomes among households within the fire perimeter with those outside of the fire perimeter. Again, we employ a difference-in-differences (DID) methodology. Similar to the pollution findings, results of the fire analyses show a near-term increase in mortgage, credit card, and personal loan delinquency among consumers in the fire zone. Further, adverse household fire treatment effects typically persisted multiple quarters after the fire. As above, to better understand the delinquency results, we use proprietary information from the Federal Reserve's Y-14M consumer data base to study credit card spending, repayment, and monthly balance in the wake of the extreme wildfires. Interestingly, we find that post-fire, on average, treated households in the fire zone increased spending but paid down credit card debt even more, resulting in a decline in monthly balance. At the same time, results indicate a sizable increase among fire-treated households in credit card past due. While the combination of reduced credit card indebtedness (repayment in excess of spending) and increased delinquency and past due may seem puzzling, further analysis revealed that the reduction of credit card balance occurred largely among homeowners, whereas increased credit card delinquencies were evidenced among the renter population, especially those with lower credit scores.

Fire damage typically is covered by homeowner's insurance. In recent years, while wildfire-related insurance in California sometimes has been excluded from the standard homeowner's insurance policy, the State of California has made fire coverage available via the California FAIR Plan (Biswas et al., 2023).[2] Among homeowners, the limited estimated adverse household financial impacts (including paydown in credit card balances post-wildfire) likely reflects use of funds from payout of insurance claims, consistent with findings from the flood disaster literature (Gallagher and Hartley (2017), Billings et al. (2022)). In contrast, renters typically receive little in the way of fire insurance payout and may experience financial distress owing to use of their own limited resources to cope with adverse fire effects, including work disruption as well as event-related health expenses.

[2]The California FAIR Plan provides basic insurance to satisfy the lender requirement that the home be insured against the risk of fire. While the FAIR Plan policy covers damage from fire, smoke, lightning, 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.

Per above, estimation results indicate that both dispersed wildfire-attributed pollution events and proximate burn zone fire events are associated with statistically elevated and economically salient increases in mortgage, credit card, and personal loan delinquency. Findings from the Camp Fire indicate a 20 percent increase in the likelihood of credit card past due among those exposed to fire-related particulate emissions and pollution events, compared to an average 50 percent increment in the likelihood of credit card past due among burn zone households. The estimated widely dispersed pollution treatment effects are highly salient, however, given the substantially larger geographies and populations treated by far-flung wildfire-related emissions. As detailed below, if we conservatively impute estimated pollution effects of the Camp Fire to the 19 million people in the New York Metro Area exposed to similarly elevated levels of smoke and pollution in the wake of the 2023 Canadian wildfires, a back-of-the-envelope calculation suggests that affected households incurred an incremental \$6 billion in credit card spending and an added \$10 billion in credit card debt.

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. There are also a limited number of papers that evaluate the effect of air pollution on housing and credit outcomes.[3] We advance the literature by compiling unique and detailed data so as to estimate the effects of extreme wildfires and wildfire-attributed air pollution on a broad array of household financial outcomes. For example, both burn zone and broadly dispersed wildfire-induced air pollution result in increased delinquencies in personal and retail debt as well as higher levels of

[3] 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 of 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 $PM_{2.5}$ reduces the average rent by 0.7%.

mortgage and credit card debt. We also find interesting heterogeneity in treatment effects, whereby estimated effects of extreme wildfires on credit card debt and repayment differ among homeowners and renters, likely owing in part to the provision of damage-related insurance payouts to homeowners with damaged properties in the fire 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 economic rendering 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 our empirical strategy to estimate the smoke effects and report our results, whereas Section IV compares our estimates of smoke effects to those of the direct fire effects. Section V concludes.

II. Data

A. *Data on Wildfires*

We employ information on extreme wildfires compiled by the U.S. Department of Homeland Security National Incident Management System/Incident Command System (ICS) and processed by St Denis et al. (2020). The data include fire event information on number of structures destroyed, burned acres, injuries, and fatalities.[4] We utilize the most recent 2016 - 2020 version of the data. To identify wildfire burn perimeters, we link the ICS data to the U.S. Forest Service Monitoring Trends in Burn Severity (MTBS) database, which documents the spatial footprint of the wildfires (Eidenshink et al., 2007). For sampled wildfire events, we identify the census

[4]For more information, see McConnell et al. (2021).

blocks/tracts/zip codes included in the fire burn perimeter and beyond.

The analysis focuses largely on the 2018 Camp Fire, the most extreme wildfire to date in terms of structure damage. We also include in the analysis extreme wildfires that destroyed more than 1,000 structures. Those fires account for roughly 3 percent of recent wildfires.[5] Those wildfires, like the vast majority of the extreme wildfires in the U.S. to date, occurred in California. Table A.1 provides a list of recent extreme U.S. wildfires and number of structures destroyed. We further limit the analysis to fires that occurred at least 6 quarters pre-COVID-19 to assure that pandemic effects do not contaminate our estimates of household credit outcomes. Accordingly, our sample is comprised of four extreme wildfires in California between 2016 and 2020, namely the Camp Fire, the Carr Fire, the Thomas Fire, and the LNU Complex Fires. The geography of the four sampled fires is mapped in Appendix Figure A.1; further, we zoom in on the Camp Fire only in Figure A.2. 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 prior to and after the wildfire event. Summary statistics are reported for average outcomes for the set of four sampled extreme 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).[6] 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

[5] McConnell et al. (2021) show that only extreme wildfires had an effect on household financial outcomes.

[6] These data come 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 U.S..

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 census tract level and zip code level for each day of the sample period. Our primary measure of smoke exposure is an indicator of whether a tract is fully covered by a smoke plume on a given day.

C. ***Pollution Data***

We obtain ambient air pollution data from the EPA's Air Quality System. We use daily ground monitor readings for EPA "criteria pollutants," including a measure of particulate matter ($PM_{2.5}$). To measure air pollution for an area, we take the distance-weighted average of two or three valid readings for each pollutant from monitors closest to an area's centroid. We spatially intersect these data with census tract and zip code tabulation area boundary files and link them to individual-level administrative records.

We also employ pollution data from the Stanford Echo Lab (see Childs et al. (2022)), which derive from a machine learning model of daily wildfire-driven $PM_{2.5}$ concentrations based on a combination of ground, satellite, and reanalysis data sources. The authors generate daily estimates of smoke $PM_{2.5}$ over a 10 km-by-10 km grid for the contiguous U.S. from 2006 to 2020.[7] Table A.3 provides summary statistics for smoke and pollution for our sampled areas. Figure 1 shows the monthly average smoke-$PM_{2.5}$ predictions by Stanford Echo Lab for the month prior to the Camp Fire, the month of the fire, and the month following the fire. Figure 1 shows a sharp increase in wildfire smoke pollution during the month of the Camp Fire. During that month, many zip codes

[7]Childs et al. (2022) find that the number of people in locations with at least one day of smoke $PM_{2.5}$ above 100 $\mu g/m^3$ 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. For more information, see `https://www.stanfordecholab.com/wildfire_smoke`.

in a radius of 100 miles from the Camp Fire experienced heavy pollution, i.e. defined as those with average daily $PM_{2.5}$ greater than 40 $\mu g/m^3$.

D. *Credit and Consumer Spending Data*

We measure household credit outcomes using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP). The CCP is a nationally representative 5% random sample of individuals with a credit report.[8] The panel provides detailed credit-report data for (anonymous) individuals and households in quarterly increments beginning in 1999. 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).

In order to contrast outcomes across housing tenure status (homeowners vs renters), we turn to the Credit Risk Insight Servicing McDash (CRISM) data. CRISM is an anonymous credit file match from Equifax's full population of consumer credit reports (as compared to the 5 percent random sample of the CCP) to the Black Knight McDash loan level mortgage dataset.[9] Hence, 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 rather than quarterly, as in the CCP.

To supplement the CCP data, we obtain account-level information on consumer credit card activity from the Federal Reserve Y-14M regulatory reports. In addition to its higher frequency, the monthly Y-14M data have the important advantage of including detailed credit card spending,

[8]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.

[9]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.

repayment, 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 limit of the credit card account, age of the account, contemporaneous interest rate, and borrower geographic location at the 9-digit zip code.[10] The data also contain credit performance information, including an account past due indicator. See Agarwal et al. (2020) for more information. The Y-14M credit card data are available from June 2013. For purposes of our study, we use data from January 2016 to December 2020, centering around the month of each wildfire in our analysis.

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

A. *Research Design*

To estimate the effects of wildfire-attributable air pollution on household financial outcomes, we 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 the wildfire burn perimeter and its close proximity (e.g., we exclude zip codes within the burn zone or up to 5 miles from it's perimeter) to avoid burn and related fire spillover effects. Instead, we focus on zip codes that are 5- to 30-miles from the wildfire boundary. For purposes of robustness, we also evaluate smoke and pollution effects at distances of 50 and 100 miles from the fire perimeter. We classify zip codes at distances from the fire perimeter of 5- miles and beyond based on the level of pollution in the four weeks immediately following the onset of the fire and then divide those zip codes into three groups: heavily polluted zip codes defined as those with

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

average daily $PM_{2.5}$ greater than 40 $\mu g/m^3$; moderately polluted zip codes defined as those with average daily $PM_{2.5}$ less than 40 $\mu g/m^3$ but more than 5 $\mu g/m^3$; and lightly polluted zip codes defined as those with average daily $PM_{2.5}$ less than 5 $\mu g/m^3$.[11] Our treatment group is comprised of the heavily polluted zip codes; our control group includes the lightly polluted zip codes; and the remaining moderately polluted zip codes are excluded from the analysis. We test different $PM_{2.5}$ cutoffs to ensure robustness in results. On the time dimension, we define the sample to include the five to eight quarters, depending on data availability, before and after each fire. We estimate the following model:

$$Y_{i,t} = \gamma * Pollution_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}, \tag{1}$$

where $Y_{i,t}$ is the outcome measure for individual/account i at time t (quarterly frequency for the CCP and monthly frequency for the 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 heavy pollution 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 Equifax Risk Score or 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 $PM_{2.5}$ levels and baseline $PM_{2.5}$ levels, defined as the

[11] According to the Indoor Air Hygiene Institute, "most studies indicate $PM_{2.5}$ at or below $12\mu g/m^3$ is considered healthy with little to no risk from exposure. If the level goes to or above $35\mu g/m^3$ during a 24-hour period, the air is considered unhealthy and can cause issues for people with existing breathing issues such as asthma."

same month $PM_{2.5}$ levels in the prior three years. Here the empirical model is:

$$Y_{i,t} = \gamma * \Delta PM2.5_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{2}$$

We also estimate the effect of fire-induced air pollution on household financial outcomes using an instrumental variable approach. Again, the concern is that the level or change in air pollution as measured by PM2.5 may reflect factors beyond wildfire-related smoke, notably including economic activity in the study area, so as make the PM2.5 measure endogenous to the economic outcomes we study. An instrument that we consider is the number of heavy smoke days in an area. In fact, in Figure A.3, we demonstrate how days of wildfire smoke caused PM2.5 to increase significantly in the aftermath of the fire. As is evident, in the aftermath of the Camp Fire, and among zip codes treated by wildfire-related smoke, pollution levels increased sharply, to 60 $\mu g/m^3$. This finding corroborates estimates of Childs et al. (2022) at the Stanford Environmental Changes and Human Outcomes (Echo) Lab, who develop a machine learning model to estimate wildfire smoke-driven pollutants for the contiguous U.S. from 2006 to 2020. The method and data utilized by Childs et al. (2022) are more sophisticated than those associated with the above smoke days event study regression (see Figure A.3). As the Stanford Echo Lab estimates are likely to more accurately attribute PM2.5 to wildfire smoke, we use their estimates of wildfire smoke-related $PM_{2.5}$ in the second stage of our IV regression:

$$Y_{i,t} = \gamma * \widehat{PM2.5}_z * Afterfire_{z,t} + X_{i,t}\vec{B} + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{3}$$

Here the $\widehat{PM2.5}_z$ are the zip code-level daily estimates obtained from the Stanford University ECHO Lab aggregated to monthly frequency.[12] In order to evaluate how wildfire-induced air

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

pollution dissipates over time, we also run event-study type of regressions in a similar difference-in-differences setting.

B. Estimated Effects

In this section, we present estimates of the effect of wildfire smoke-attributable air pollution on consumer credit outcomes. As discussed above, expansive geographies and large populations beyond the actual burn perimeter may be treated by wildfire-attributable smoke and air pollution. Indeed, heavy smoke and pollution emissions from the roughly 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.

In Table 1, we report 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 heavy pollution, above 40 $\mu g/m^3$, i.e. our treatment group, to those residing in zip codes with light pollution, below 5 $\mu g/m^3$, i.e. our control group, before and after the Camp Fire. Panel A of the table shows estimates of pollution effects using year-over-year changes in $PM_{2.5}$ as specified in equation 2. The time frame of the analysis is two years prior to and 14 months after the Camp Fire (until the start of the COVID-19 pandemic). Columns 1 and 2 in Panel A show no significant increase in the likelihood of mortgage and credit card delinquencies for the treatment group in the wake of exposure to high level of wildfire-attributed air pollution. However, Columns 3 and 4 show that exposure to high levels of pollution results in increases in personal loan and retail/store card delinquencies. The estimated effects are sizable: Borrowers exposed to higher levels of wildfire-related air pollution, on average, experienced an increase in personal loan delinquency and retail/store card delinquency of 5 and 3 percentage points, respectively, relative to those exposed to lower levels of wildfire-induced air pollution.

In Panel B of Table 1, we present results of IV estimation, as specified in equation 3. Estimates are qualitatively consistent with those shown in Panel A. Higher levels of wildfire-related air pollution result in statistically and economically elevated personal loan and retail/store card delinquency. Further, as shown in Panel B of Table 1, we find a statistically and economically elevated rate of credit card delinquency. Column 2 shows that on average, borrowers exposed to higher levels of wildfire-related air pollution experienced an increase in credit card delinquency of 0.4 percentage points, respectively, relative to those exposed to lower levels of wildfire-induced air pollution. In the case of mortgages delinquency, the IV approach does not yield precise estimates of the effects of wildfire-attributed air pollution on credit outcomes.

In Appendix Table A.4 , we assess robustness of results to more distant diffusion of wildfire-related smoke and pollution. There, we report on household credit delinquencies due to wildfire-related smoke and pollution at distances of 30-50 and 50-100 miles. As would be expected, the estimated coefficients are larger for 30-50 miles than for the 50-100 miles from the fire perimeter. The results are robust to those presented in Panel A of Table 1 for zip codes that are 30 to 50 miles from the Camp Fire. Table A.3 contains summary statistics on smoke and pollution for sampled areas.

Table 2 shows the effects of Camp Fire-induced air pollution on credit card usage and credit performance, using data from the Federal Reserve Y-14M. Panel A of the table shows estimates of pollution effects using year-over-year changes in $PM_{2.5}$ as specified in equation 2. The outcome variables include monthly measures of credit card spending, repayment, account 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 borrowers exposed to higher levels of wildfire-related air pollution, on average, increase their spending by $730 on an annual basis relative to those exposed to lower levels of wildfire-induced air pollution. Also, repayment of credit card debt among treated households was $521 less on an annual basis. As a result, treated households accumulated roughly $1400 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., likely owing in part 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 wildfire-attributed air pollution showed a 4.6% elevated likelihood of having an account past due. This finding is economically significant, given an average rate of account past due of 13.7%.

In Table 2 Panel B, we present the results of our IV estimation, as specified in equation 3. Estimates are consistent with those shown in Panel A. Again, borrowers exposed to heavy wildfire-induced air pollution engaged in higher levels of credit card spending and lower levels of credit card debt repayment. Treated borrowers also accumulated more credit card debt and were more likely to have a credit account past due. As discussed above, the regression models include substantial controls such as highly granular fixed effects and time-varying borrower attributes (including time-varying borrower credit scores and account current credit limits). We also test different $PM_{2.5}$ cutoffs in constructing the control and treatment groups and find results to be highly robust.

In Appendix Table A.5 we assess robustness of credit card results to more distant diffusion of wildfire-related smoke and pollution. There, we evaluate the effects of Camp Fire-induced pollution on credit card spending and repayment, at distances up to 100 miles from the Camp Fire. Panel A in Appendix Table A.5 reports results up for 30-50 Miles from the Camp Fire, whereas Panel B reports results for 50-100 miles. Consistent with results presented in Table 2, findings show statistically and economically elevated levels of credit card spending due to diffusion of wildfire-related pollution at distances of 30-50 and 50-100 miles from the fire perimeter. That said, we find no significant effects of distant diffusion of wildfire-related smoke and pollution (at distances up to 100 miles from the Camp Fire) on credit card payments and past due.

Table 3 reports on heterogeneity in smoke effects among population stratified by credit score. 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 super-prime borrowers and borrowers with high credit limits. Those borrowers are likely higher income borrowers, and thus likely have the capacity to spend more on preventive measures to combat air pollution induced by the wildfire.

In Appendix Table A.6 , 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 relatively heavy air pollution spend more and repay less, compared to those exposed to low or no pollution.

In Figure 2, we plot the time-varying effects of wildfire-induced air pollution on credit card usage. In the initial two quarters following a wildfire, we see a marked increment in credit card spending. The estimated effect remains elevated in the third quarter but tends to dissipate over time. We also see clear accumulation of credit card balance in the quarters after the wildfire for those who were exposed to heavy air pollution.

C. ***Potential Mechanism***

The existing literature points to potential channels through which wildfire smoke may affect household financial health. First, elevated wildfire smoke and pollution may result in health disability and higher levels of health-related spending. Among the most widely documented adverse effects of ambient air pollution are those associated with health, including increases in both hospitalization and premature mortality among children and the elderly (Chay and Greenstone (2003), Jayachandran (2009), Chen et al. (2013), Deryugina et al. (2019), Anderson (2020)). Approximately one-third of U.S. households include someone with an existing respiratory health condition at risk of serious medical complications in the wake of prolonged exposure to the fine particulate matter ($PM_{2.5}$) found in smoke (McCaffrey and Olsen (2012). Hence households may experience adverse health outcomes and incur related medical or preventative health spending as a result of extreme wildfire-attributable smoke and particulate pollution events.

Second, wildfire-related smoke and pollution may affect household finances via an employment and income channel. Employment and work interruptions also may reflect the adverse health impacts of extreme smoke and pollution events as described above. Smoke events may lead to work interruption: (Borgschulte et al., 2022) find that a day of county wildfire smoke exposure reduces quarterly per capita earnings by $5.20, representing a roughly 0.10 percent reduction in quarterly mean earnings of $5,359.70. Borgschulte et al. (2022) also report that each day of wildfire smoke reduces quarterly county employment by about 80 per million people, a 0.013 percent decline relative to the sample average employment rate of 62.6 percent. Chang et al. (2019) study call center workers in a large urban city in China and find that a 10-unit increase in the city's daily Air Pollution Index leads to a decrease of 0.35 percent in worker output.[13] Similarly, (Addoum et al., 2023) report on business loss in the immediate aftermath of a wildfire-related pollution event.

Given the above discussion, we below provide corroborating evidence of the effects of wildfire-related smoke and particulate air pollution on health outcomes. We start by documenting the effect of wildfire-attributable increases in ambient smoke and particulate air pollution on deterioration in respiratory status and related mitigants using Google search data. Figure 3 shows marked increases in Google Trends internet search for air purifiers as well as elevated concerns regarding smoke

[13] Adhvaryu et al. (2019) study the effects of air pollution on garment manufacturing worker productivity in India, and show that each 10-unit increase in hourly $PM_{2.5}$ reduces worker output by 0.5 percent.

inhalation in the immediate aftermath of the Camp Fire.

Next, we employ a methodology similar to the smoke analysis specified in Equation 3 to assess the effects of wildfire- induced air pollution on hospital emergency visits. Specifically, the outcome measures include number of emergency department visits for children and number of emergency department visits for individuals with asthma. Here the pollution term per above is coded at the county level. The difference-in-differences analysis includes both county and year-month fixed effects. The time frame of the analysis is the 14 months before and after the extreme wildfire.

We report our estimates of the Camp Fire-induced pollution effects in Table 4. In the wake of the Camp Fire, we see an increase in those adverse health indicators among counties that experienced high levels of pollution compared to counties experiencing light pollution. Our results are consistent with findings of Miller et al. (2017). That study uses detailed Medicare data to show that wildfire smoke increases both hospital admissions and outpatient ER visits.[14] The above documented Google search and adverse health effects of wildfire-related smoke and pollution suggest a channel by which air pollution events may affect household spending, indebtedness, and financial distress.

IV. Wildfire Smoke and Pollution vs Wildfire Burn Effects

We seek to complement the above estimates of household financial effects of wildfire-attributable dispersed smoke and pollution events with those associated with direct proximate fire zone damage. To that end, we require estimates of burn zone fire effects for the identical set of extreme wildfire events, timeframes, and household financial datasets and outcomes as analyzed above. The combination of those estimates would enable a broader and more complete discussion of household

[14] Our findings are also consistent with the Agency for Healthcare Research and Quality analysis of state inpatient and emergency department databases in California documenting an increase in smoke inhalation and emergency room visits after the Camp Fire. Seehttps://hcup-us.ahrq.gov/reports/ataglance/HCUPAnalysisCA2018Wildfires.pdf.

financial effects of extreme wildfire events, inclusive of both direct localized burn and far-flung pollution impacts.

While there exists some pre-existing literature on the impact of wildfires on housing and consumer financial outcomes, the empirical evidence is mixed. For example, for mortgage performance, Issler et al. (2020) find little impact of wildfires on household finance. Biswas et al. (2023) find some evidence of elevated mortgage delinquencies only among damaged properties in fire burn areas. McConnell et al. (2021) indicate that consumer credit distress, including loan delinquency, personal bankruptcy, and home foreclosure, improve rather than deteriorate in the aftermath of a wildfire, but that the changes are not statistically significant. The sometimes counter intuitive results in the existing literature might owe to the commingled effects in the data of fire damage, insurance payouts, and other mitigants. On the one hand, wildfires may result in destruction of physical property and disruption of work so as to result in household financial distress. However, compensation of household economic loss via wildfire or standard homeowners insurance may mitigate financial distress. Further, governmental and philanthropic emergency assistance may help to dampen adverse financial effects.

A. ***Research Design***

We 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:

$$Y_{i,t} = \beta * Fire_{b,t} * Post_{b,t} + \tau_t + \zeta_i + \varepsilon_{it}, \tag{4}$$

Where $Y_{i,t}$ is the outcome measure for individual i in time t (quarterly for CCP and monthly for CRISM). The $Fire_{b,t}$ term is a dummy variable that takes on the value of one if the individual resides in a census block b in the fire zone and zero if the individual resides in census block whick is proximate to the fire zone but outside the fire perimeter (1 - 5 miles from the fire perimeter). The categorical term $Post_{b,t}$ takes on the value of 1 in the aftermath of the fire event and 0 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 in frequency at the individual credit card account-level. An advantage of the Y-14M is that we observe not only delinquencies and balance information as in the CCP and CRISM but also credit card spending, repayment, and balance at the monthly account level. The granularity of the data further allow us to include two-way fixed effects. As discussed above, we control for time-varying account attributes.

To estimate fire effects, we distinguish between treated areas within the fire perimeter and control areas up to 5 miles beyond the fire perimeter. Note that the entire spatial footprint of the wildfire burn analyses, both within the fire perimeter and among the proximate control areas is treated by fire-related smoke. Hence, our fire area study design enables us to difference out and identify burn zone fire effects.

B. ***Estimated Wildfire Effects***

Table 5 reports on the effects of the Camp Fire on consumer financial distress as estimated in a difference-in-differences framework following equation 4. Per above, our treated group is comprised of consumers living in census blocks within the Camp Fire burn footprint, whereas the control group includes consumers living 1-5 miles from the fire perimeter. As in the case of our smoke and pollution analysis, the outcome terms in columns 1-4 include mortgage delinquency, credit card delinquency, personal loan delinquency, and retail/store card delinquency, respectively. Columns 1-3 indicate that the Camp Fire resulted in statistically significant increases in mortgage, consumer credit card, and personal loan delinquencies. For example, Column 2 shows that consumers living in the burn zone experienced an additional 2 percentage point (pp) increase in credit card delinquency following the Camp Fire, compared to consumers not directly affected by the fire (those living 1-5 miles from the fire perimeter). This effect is economically significant given an average credit card delinquency rate of about 4 percent in our sample. All regressions include year-quarter and consumer fixed effects.

Table 5 provides estimates of average treatment effects of the Camp Fire on consumer financial distress over the eight quarters following the fire. In Figure 4, we apply our difference-in differences framework to estimate quarterly and plot the treatment effects of the fire. Panels A-D show estimated effects on consumer total delinquency (delinquencies across all credit accounts), mortgage delinquency, credit card delinquency, and personal loan delinquency, respectively. Findings indicate that adverse estimated effects of the wildfire on credit card delinquency persisted over the full two year post-fire period.

To better understand the effects of the wildfire on credit card delinquencies, we turn next to the Federal Reserve Y-14M credit card data. We follow the same difference-in-differences approach using the account-month panel. Per above, the Y-14M data further allow us to include granular fixed effects and other time-varying controls.

In Table 6, we report on estimates of the effects of the Camp Fire on credit card spending, payment, balance, and past due in columns 1-4, respectively. These analyses conform to those undertaken for Camp Fire-related distant smoke and pollution. To account for possible seasonality, we use year-over-year changes in the dependent variables. Changes in credit card spending, repayment, and balance, as shown in the first three columns, are annualized dollar amounts. As shown in the table, borrowers residing in the wildfire burn area engaged in roughly $1,670 per annum in additional spending in the 14 months following the fire, relative to borrowers residing 1-5 miles outside the burn area (column 1). Interestingly, estimates also show that fire zone residents engaged in about $2,350 per annum more 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 $2,370 per annum less in credit card debt (column 3). Column 4 of Table 6 shows an elevated account past due among borrowers residing in the wildfire burn area, consistent with the increased credit card delinquency result reported in the CCP analysis discussed above.

In Figure 5, we plot quarterly estimated effects of the Camp Fire on credit card spending and balance. Results show a clear increase in credit card spending but a decline in balance (due to repayment) in the immediate aftermath of the wildfire among borrowers residing in the fire zone. The increases in spending peaked in the second quarter post-fire and then tapered in quarters 3-5.

The combination of reduced credit card indebtedness (repayment in excess of spending) and increased delinquency/past due shown in Tables 5 and 6 appears puzzling. A possible explanation is that that homeowners whose property was damaged by the fire used payouts from insurance claims to reduce debt inclusive of credit card balance, whereas households who did not receive insurance payout were more likely to become delinquent in their payments in the wake of increased credit card wildfire-related spending.

Unfortunately, the Y-14 data does not contain information on borrower tenure status. To shed additional light here, we return to the CCP data and segment our sample into homeowners and renters.[15] We further separate high Equifax Risk Score borrowers from low Equifax Risk Score borrowers. We then repeat our difference-in-differences analysis using the segmented CCP sample. Table 7 reports our results on credit card balance (Panel A) and credit card delinquency (Panel B). Findings indicate that homeowners residing in the fire zone (and likely to have experienced property damage) paid down their credit card balance more than those in the control group (Panel A column 2). In the case of those households, results fail to show any increase in credit card delinquency (Panel B columns 1 and 2). In contrast, elevated credit card delinquencies are indicated among renters with lower Equifax Risk Scores (Panel B column 3).

The combination of findings of the above analyses suggest an interplay between fire damage and insurance payout in shaping consumer financial outcomes. Specifically, the Camp Fire caused property damage and work disruptions; in order to cope with the adverse wildfire effects, consumers engaged in more credit card spending. However, homeowners who received payout of insurance claims had greater financial capacity to pay down their debt inclusive of credit card balance. In contrast, renters lacking insurance payout had fewer financial resources to pay down their elevated credit card debt and were more likely to fall into delinquency.

While insurance claims payout data to show direct evidence of the insurance payout explanation is not available from the California Department of Insurance, our interpretation is consistent with Gallagher and Hartley (2017) findings of mortgage borrowers using flood insurance payout to pay down their mortgages. Further, the insurance explanation also supported by additional analysis displayed in Appendix Figures A.4 and A.5. In Appendix Figure A.4, we see that for borrowers who remained in the fire zone subsequent to the Camp Fire, both the number of credit card accounts

[15] In CCP, we define consumers with a 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. Therefore, we excluded renters living at the same address for more than three years to avoid counting consumers as renters if they are actually homeowners with a zero mortgage balance.

and credit card balance declined significantly in the aftermath of the fire.[16] In Appendix Figure A.5, findings from CRISM data show the decline in credit card accounts and balance was significantly larger for mortgage borrowers residing in the fire zone.[17]

When we compare the estimated effects of wildfire smoke with those of the wildfire burn several findings stand out. First, in terms of debt accumulation, if we put Figure 2 and Figure 5 side by side, findings indicate that wildfire smoke caused more spending and less repayment and thus a significant accumulation of debt (+ $2,000 at peak in the quarters after the wildfire), whereas wildfire damage in the fire zone caused more spending but also increased repayment and hence a decline in indebtness (- $5,000 at peak in the quarters after the wildfire). As discussed previously, insurance likely plays an important role in mitigating the adverse debt effects of extreme wildfires. By contrast, it is hard to insure against distant wildfire smoke.

Second, in terms of delinquencies, we find that the estimated effects of wildfire-attributable smoke and pollution on household financial outcomes (above) are not as large as those stemming directly from the wildfire itself. For example, the Camp Fire resulted in an average 50 percent increase in the likelihood of credit card past due among burn zone households, whereas distant wildfire-attributable emissions and particulate pollution associated with that same event resulted in a roughly 20 percent increase in credit card past due. That said, the far-flung smoke- and pollution-treated group is highly dispersed and comprises a substantially larger population than those directly treated by the wildfire.

[16]The number of personal loan accounts and retail store card accounts was also reduced significantly after the fire.

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

V. Conclusions

Despite the growing incidence, severity, and geography of extreme wildfires, there exists limited evidence of the effects of localized burn and related dispersed smoke and pollution events on household financial well-being. Adverse household financial effects may extend well beyond the fire perimeter and owe to substantial, far flung, and lingering wildfire-related smoke and particulate emissions. Detrimental effects of wildfire pollution events on household finance may occur via health and employment disruption channels. In this paper, we provide estimates of wildfire and attributable smoke and particulate pollution effects across a broad array of household financial and health indicators. The analysis derives from the combination of highly-articulated datasets on wildfires, wildfire-induced smoke, air pollution, and consumer financial and health outcomes.

In the analysis, we provide new estimates of the causal concentration-response relationship between wildfire-attributable air pollution and household financial outcomes. Exposure to heavy pollution results in higher rates of mortgage, credit card, and retail/store card delinquencies. Households living in zip codes with high levels of pollution attributable to the 2018 Camp Fire also demonstrated higher levels of credit card spending and lower credit card repayment. The estimated effects of wildfire-induced pollution on household credit usage and credit performance are less than those associated with wildfire-treated households within the burn zone. That said, the estimated wildfire-induced particulate pollution effects are salient to substantial population dispersed across expansive geographies beyond the burn perimeter. For example, a conservative imputation of our estimates to New York consumers adversely affected by the downwind smoke and pollution associated with the 2023 extreme Canadian wildfires suggests increments of $6 billion in household credit card spending and $10 billion in household credit card debt.[18]

[18]Smoke plumes from the Canadian wildfires resulted in heavy pollution for the 19 million residents of the New York Metro Area for a duration of roughly 4 days. The recorded daily average $PM_{2.5}$ exceeded 200 $\mu g/m^3$ in New York City on Wednesday, June 7, 2023. In comparison, the 8 million residents of the San Francisco Bay Area residents were exposed to heavy Camp Fire

Among burn zone households, we similarly find an increase in financial distress, as measured by mortgage, credit card, and personal loan delinquencies. For example, similar to estimated effects of far flung fire-related smoke and pollution, households living within the perimeter of the Camp Fire recorded an increase in rates of bank credit card delinquency of 2 percentage points compared to an average level of 4 percent. Further analyses reveal that elevated credit card delinquencies largely were associated with lower credit score renter households. In contrast, homeowners in the fire zone were able to pay off their credit card balances faster than usual, perhaps owing to payout of insurance claims.

Overall, consistent with the observation that wildfire smoke can significantly affect air quality and can travel great distances, our findings reveal that adverse household financial effects of extreme wildfires go far 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 these extreme climatic events. Future research should assess the external validity of findings to severe wildfire and related smoke and pollution events as recently evidenced in such places as eastern Canada and southern Europe.

related smoke and pollution for roughly 9-1/2 days with a peak recorded daily average $PM_{2.5}$ in San Francisco of 177 $\mu g/m^3$ during the 2018 Camp Fire. We discounted the Camp Fire point estimate by roughly 60 percent to account for the reduced duration of the Canadian wildfire pollution effects. Note that an incremental $10 billion in annualized consumer credit card debt is roughly equivalent to 1 percent of the $1 trillion in credit card debt outstanding.

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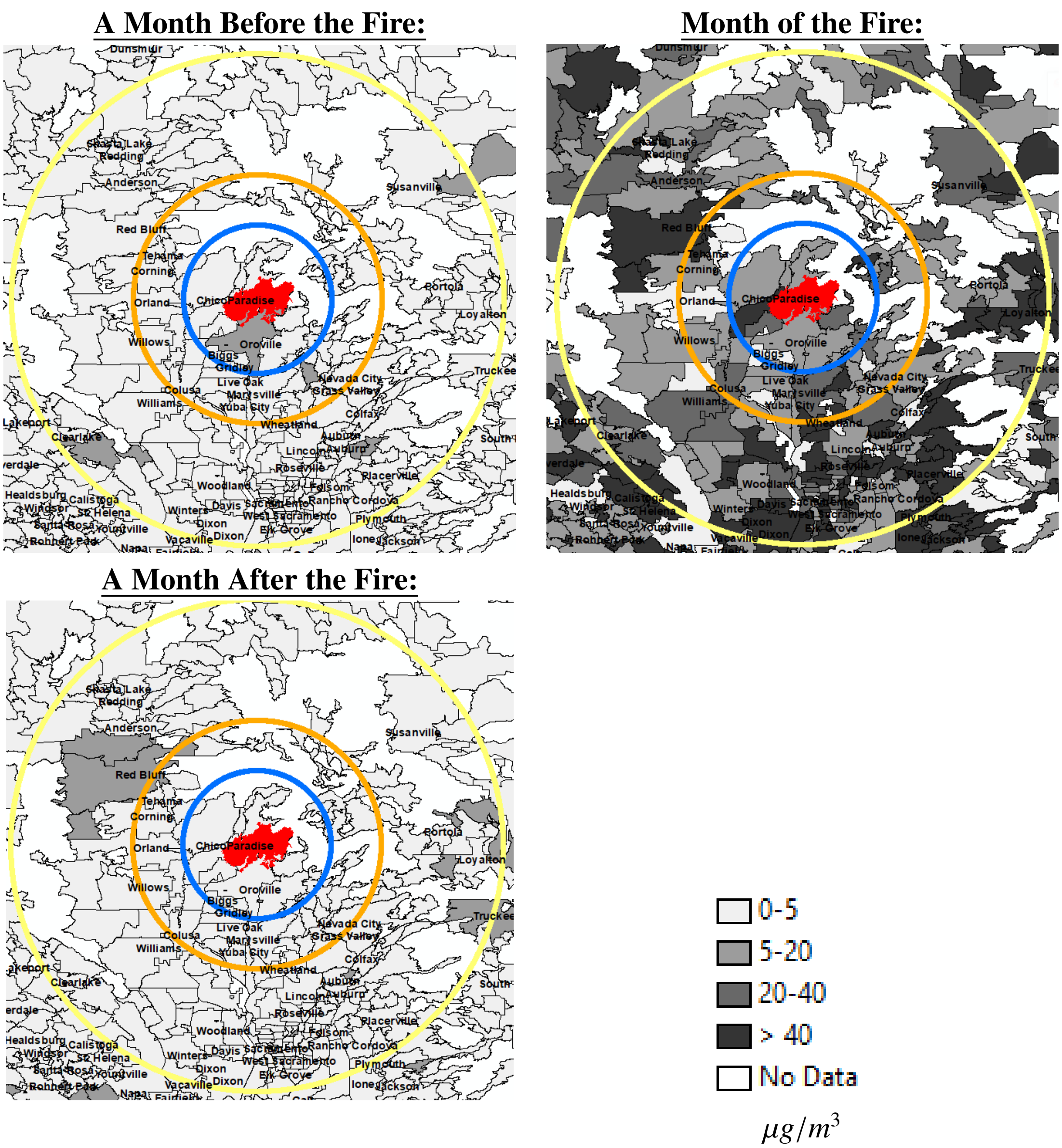
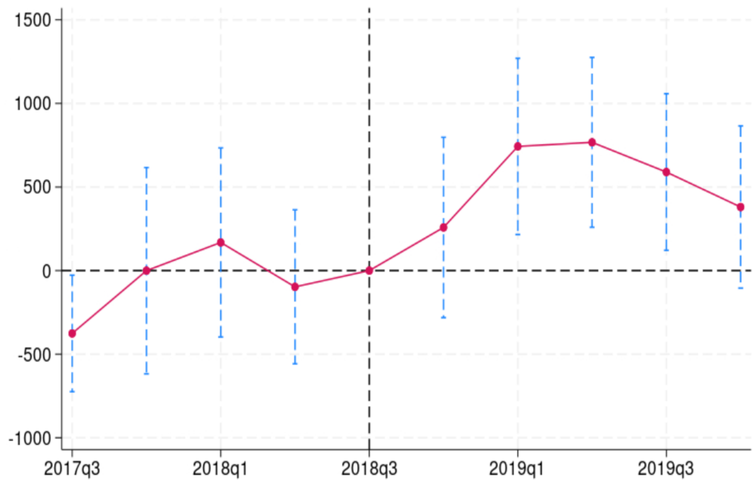
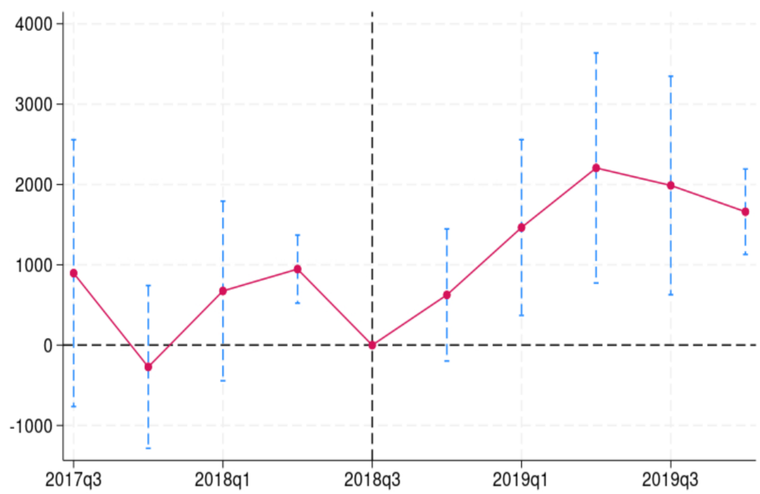


Figure 1. Monthly Average PM2.5 from Smoke around the Camp Fire

Notes: This figure shows the variation in the machine learning index produced by Stanford Echo Lab of wildfire-driven PM2.5 concentrations using a combination of ground, satellite, and reanalysis data sources. This index generates estimates of smoke $PM_{2.5}$ a month before and after the Camp Fire. The red area is the Camp fire footprint. The first blue circle is a radius of 30 miles from the fire, the orange circle is 50 miles, and the yellow circle is 100 miles from the fire. The border lines are zip codes. Each zip code is colored in gray according to the monthly average of smoke-$PM_{2.5}$ predictions. Sources: Stanford Echo Lab and Childs et al. (2022).



Panel A Credit card spending



Panel B Credit card balance

Figure 2. Effects of Camp Fire-Induced Air Pollution on Credit Card Spending and Balance

Notes: This figure shows the temporal pattern of the estimated effect of Camp Fire-induced air pollution on credit card spending and balance 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 in zip codes that were exposed to heavy pollution (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 5 $\mu g/m^3$), before and after the Camp Fire. We include account fixed effects, year-month fixed effects and county by quarter fixed effects. Additional time-varying control variables include refreshed borrower credit score, current credit limit of the credit card account, and utilization rate. Sources: Air pollution data are from the EPA's Air Quality System and Stanford University Environmental Change and Human Outcomes (ECHO) Lab, and credit card data are from the Federal Reserve Y-14M.

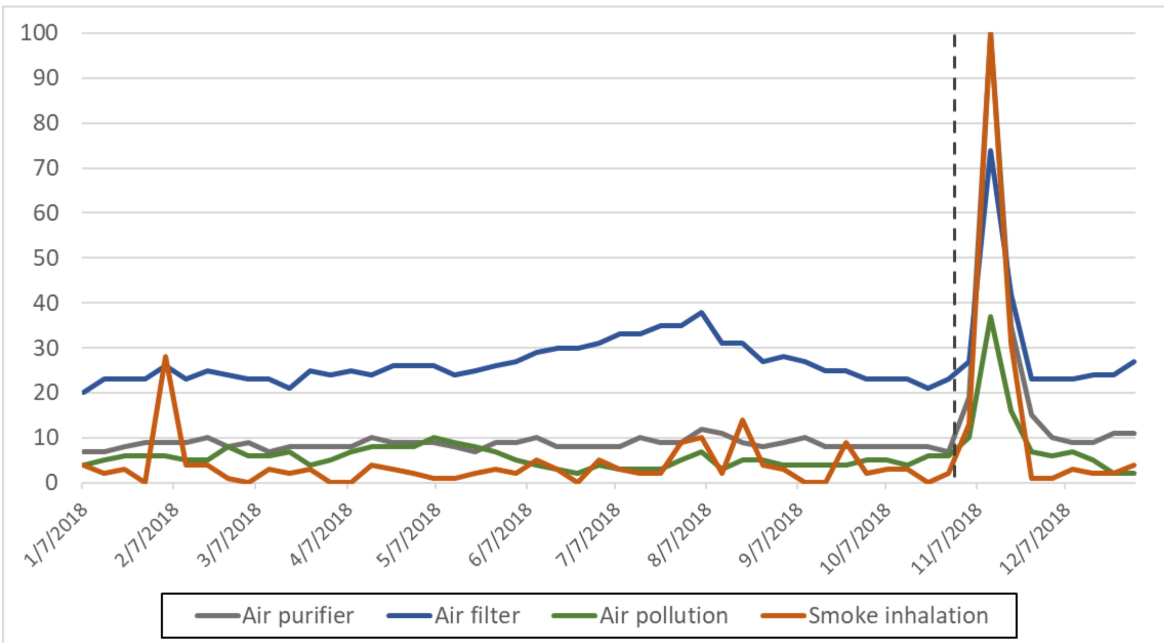


Figure 3. Effects of Camp Fire-Induced Air Pollution on Health Symptoms and Adaptation

Notes: This figure shows the temporal pattern of the estimated effect of Camp Fire-induced air pollution on real-time search indicators of spending as a response to pollution exposure and possible health effects. Using Google Trends data, we consider search keywords for adaptation, such as "Air purifier," "Air filter," and "Air pollution," and health symptoms, such as "Smoke inhalation." The vertical line represents the start date of the Camp Fire. Sources: search query data from Google Trends.

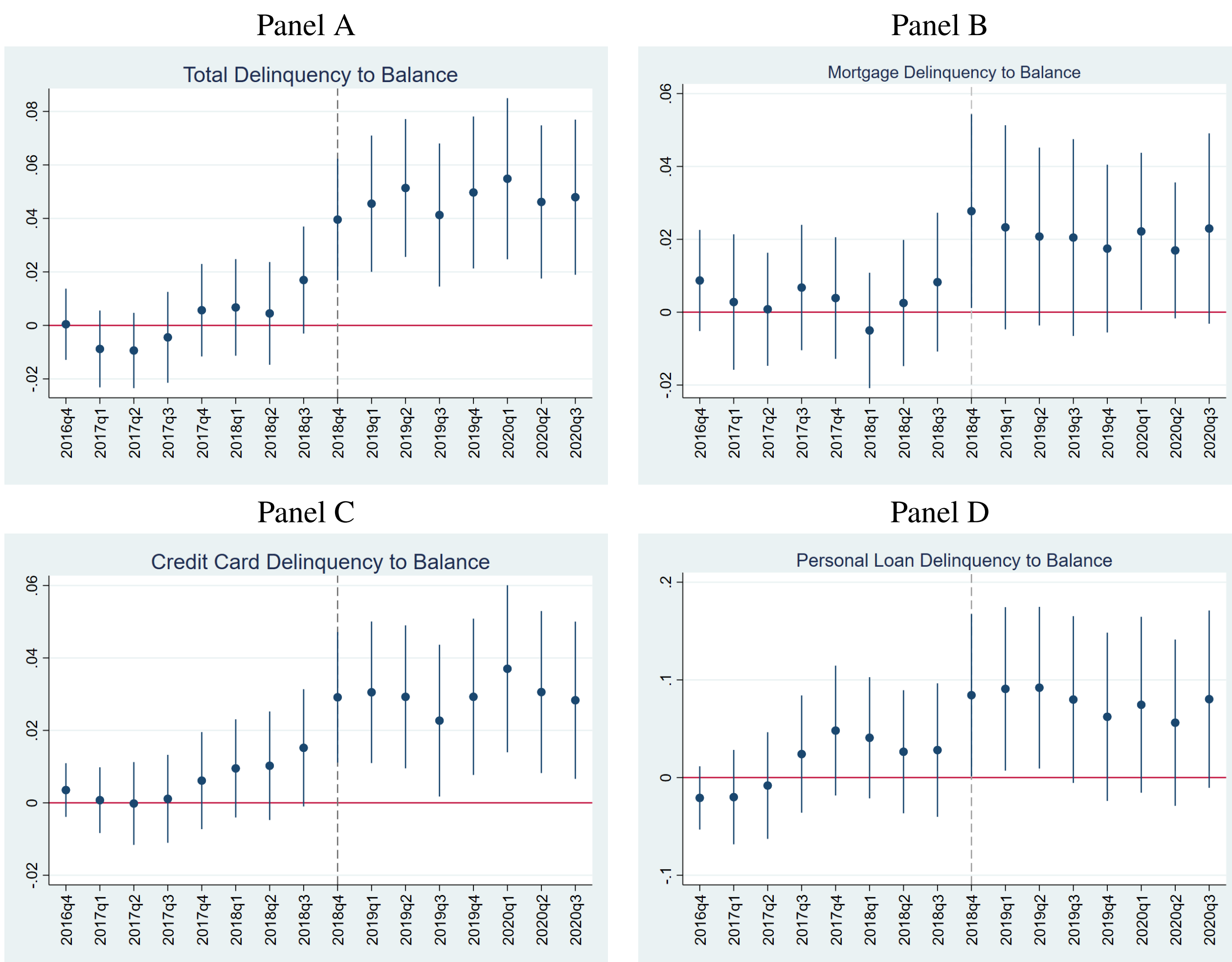
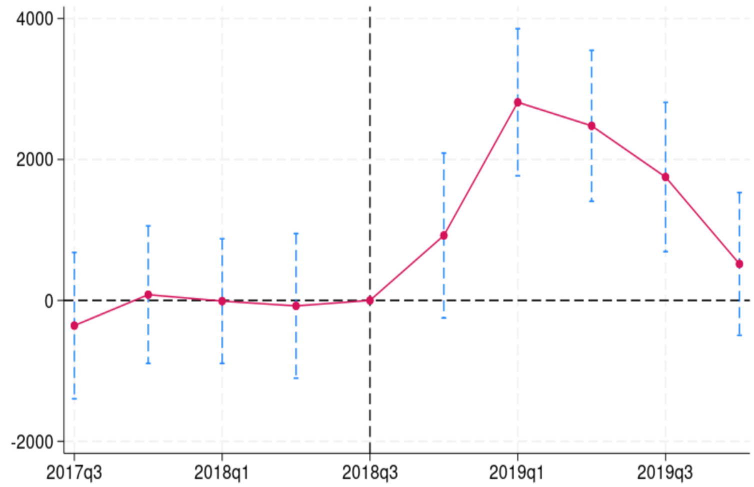
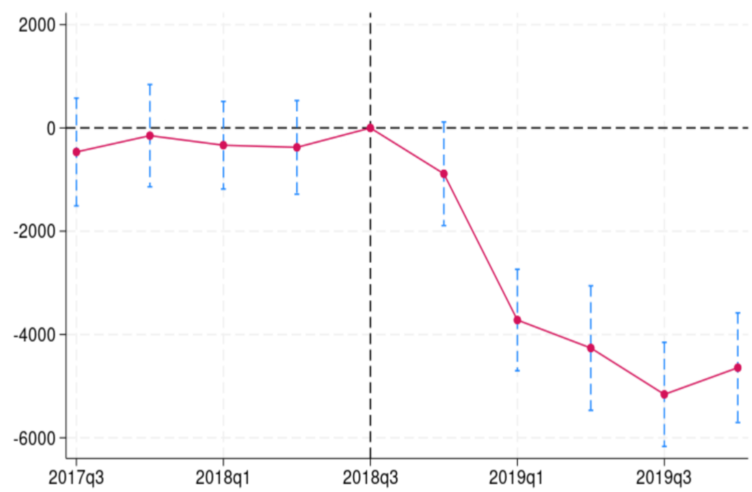


Figure 4. The Effect of the Camp Fire on Household Financial Distress

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 quarter-year and consumer fixed effects. Sources: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).



Panel A Credit card spending



Panel B Credit card balance

Figure 5. Effects of the Camp Fire on Credit Card Spending and Balance

Notes: This figure shows the temporal pattern of the estimated Camp Fire effect on credit card spending and balance 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, current credit limit of the credit card account, etc. Sources: U.S. Department of Homeland Security National Incident Management System/Incident Command System (ICS) and U.S. Forest Service Monitoring Trends in Burn Severity (MTBS) databases for fire footprint and Federal Reserve Y-14M for credit card data.

Table 1. 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 × *Post*	0.000	0.001	0.050***	0.035***
	(0.006)	(0.004)	(0.016)	(0.006)
Time-varying borrower attributes	✓	✓	✓	✓
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	60,668	184,991	38,061	53,427
R-squared	0.541	0.760	0.758	0.792
Dependent variable	0.021	0.036	0.078	0.114
Panel B: IV	Mortgage Delinquency	Credit Card Delinquency	Personal Loan Delinquency	Retail/Store Card Delinquency
Treated × *Post*	0.003	0.004*	0.025***	0.049***
	(0.004)	(0.002)	(0.007)	(0.008)
Time-varying borrower attributes	✓	✓	✓	✓
Consumer FE	+	+	+	+
Year-qtr	+	+	+	+
Observations	11,745	34,081	7,857	9,338
R-squared	0.553	0.769	0.760	0.749
Dependent variable	0.025	0.033	0.076	0.108

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 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 (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 10 $\mu g/m^3$), before and after the Camp Fire. The time frame is 14 months before and after the Camp Fire. We include consumer fixed effects and year-month fixed effects. Additional time-varying control variables include refreshed borrower credit score, and age. Robust standard errors in parentheses (error terms clustered at the county-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: EPA's Air Quality System and Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data, and Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).

Table 2. Effects of Camp Fire-Induced Pollution on Credit Card Spending and Repayment

	1	2	3	4
Panel A	Δ Spending	Δ Payment	Δ Balance	Δ Past Due
$Treated \times Post$	730.2***	-520.7***	1395.6***	0.046***
	(53.2)	(107.0)	(191.8)	(0.003)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	647,690	647,690	647,690	647,690
Adjusted R-squared	0.059	0.044	0.421	0.258
Dependent variable mean	-403.0	373.8	1,755.8	0.137
Panel B: IV	Δ Spending	Δ Payment	Δ Balance	Δ Past Due
$Treated \times Post$	612.0***	-562.7**	1363.9***	0.021***
	(127.3)	(281.0)	(102.7)	(0.005)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month	+	+	+	+
County by quarter FE	+	+	+	+
Observations	645,681	645,681	645,681	645,681
Adjusted R-squared	0.059	0.044	0.421	0.258
Dependent variable mean	-398.4	379.1	1755.3	0.136

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 (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 5 $\mu g/m^3$), before and after the Camp Fire (we have tested different PM2.5 cutoffs and found results to be highly robust). 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, year-month fixed effects and county by quarter fixed effects. Additional time-varying control variables include refreshed borrower credit score, current credit limit of the credit card account, and utilization rate. Robust standard errors in parentheses (error terms clustered at the county-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: EPA's Air Quality System and Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data; Federal Reserve Y-14M for credit card data.

Table 3. Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Payment: Different Credit Score and Credit Limit Segments

Panel A: Δ Spending	1 Credit Score ≤ 660	2 Credit Score > 780	3 Credit Limit $\leq 2,000$	4 Credit Limit $> 10,000$
$Treated \times Post$	-298.2***	682.0**	193.0***	974.6**
	(48.8)	(248.3)	(19.9)	(500.2)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	127,481	185,507	161,631	111,525
Adjusted R-squared	0.113	0.109	0.104	0.077
Dependent variable mean	-1,286.2	-45.8	-234.4	-587.9

Panel B: Δ Repayment	Credit Score ≤ 660	Credit Score > 780	Credit Limit $\leq 2,000$	Credit Limit $> 10,000$
$Treated \times Post$	-476.2*	430.2	257.4*	1031.0*
	(254.7)	(370.1)	(118.1)	(515.5)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	127,481	185,507	161,631	111,525
Adjusted R-squared	0.101	0.050	0.112	0.048
Dependent variable mean	78.8	128.0	119.9	817.9

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 and credit limit segments. We compare borrowers in wildfire-treated zip codes that were exposed to heavy pollution (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 5 $\mu g/m^3$), 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, current credit limit, and utilization rate. Robust standard errors in parentheses (error terms clustered at the county-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: EPA's Air Quality System and Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data; Federal Reserve Y-14M for credit card data.

Table 4. Effects of Camp Fire-Induced Pollution on Health Outcomes

	1 Emergency Visits - Kids	2 Number of Asthma ED Visits	3 Emergency Visits - Kids	4 Number of Asthma ED Visits
$Treated \times Post$	3,149* (1,068)	1,153* (689.1)		
$DeltaTreated \times Post$			1,298* (733.2)	1,153* (689.1)
County FE	+	+	+	+
Year-month FE	+	+	+	+
Observations	264	212	228	220
R-squared	0.753	0.15	0.536	0.432
Dependent variable mean	122,222	148	122,222	148

Notes: This table shows the effect of wildfire-related air pollution on health outcomes 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 counties exposed to heavy pollution (pollution level above the 75 percentile), and are marked as $Treated$ to those exposed to light pollution (pollution level in the bottom quartile), before and after the Camp Fire. The variable $DeltaTreated$ is defined using the *change* in pollution using the pollution level in the same county in the prior three years before the Camp Fire as the baseline (here, again, treated counties are those that experienced an *increase* in pollution in the upper quartile). The time frame is 14 months before and after the Camp Fire. Robust standard errors in parentheses (error terms clustered at the county level). ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: EPA's Air Quality System for air pollution data; California Health and Human Services Open Data Portal and Kids Data Portal for health data.

Table 5. 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 Consumer Credit Panel/Equifax data (CCP).

Table 6. Effects of the Camp Fire on Credit Card Spending and Repayment

	1 Δ Spending	2 Δ Payment	3 Δ Balance	4 Δ Past Due
$Treated \times Post$	1673.4***	2345.1***	-2367.4***	0.074***
	(103.7)	(121.4)	(312.3)	(0.009)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
Observations	342,746	342,746	342,746	342,746
R-squared	0.063	0.048	0.221	0.258
Dependent variable mean	-308.7	588.6	1610.4	0.136

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, current credit limit of the credit card account, etc. Robust standard errors in parentheses (error terms clustered at the zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: U.S. Department of Homeland Security National Incident Management System/Incident Command System (ICS) and U.S. Forest Service Monitoring Trends in Burn Severity (MTBS) databases; Federal Reserve Y-14M for credit card data.

Table 7. Heterogeneous Effects of Camp Fire on Credit Card Balance and Delinquency

	Homeowners		Renters	
	1	2	3	4
Panel A: Credit Balance	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720
$Treated \times Post$	-1,115.22	-1,401.26***	-522.10	-195.61
	(845.81)	(474.45)	(319.48)	(640.36)
Time-varying borrower attributes	✓	✓	✓	✓
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	637	4,358	3,009	1,528
R-squared	0.98	0.90	0.97	0.92
Dependent variable mean	7,743.2	3,784.3	2,949.9	2,021.5
Panel B: Delinquency	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720
$Treated \times Post$	0.01	0.00	0.09***	0.00
	(0.00)	(0.00)	(0.02)	(0.00)
Time-varying borrower attributes	✓	✓	✓	✓
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	3,213	16,434	8,692	3,102
R-squared	0.80	0.60	0.73	0.08
Dependent variable mean	0.01	0.00	0.06	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 were defined as those with a positive mortgage balance. We excluded renters living in the same address for more than three years to avoid counting consumers as renters if they are actually homeowners with a zero 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 Consumer Credit Panel/Equifax data (CCP).

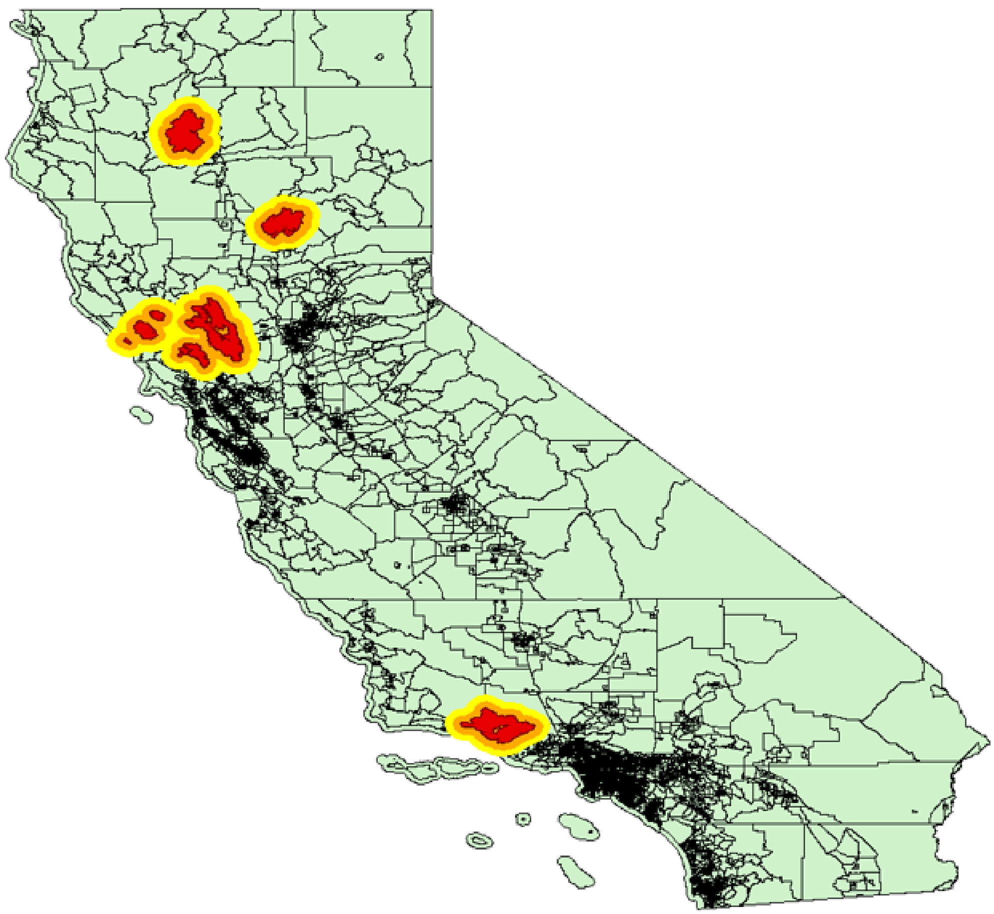


Figure A.1. Extreme Wildfires in California between 2016 and 2020 and the 1-, 5-, and 10-Mile Peripheral Rings

Notes: This figure shows the geographic location of the extreme wildfires (with more than 1,000 destroyed structures) in California between 2016 and 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. Source: U.S. Forest Service Monitoring Trends in Burn Severity (MTBS) database.

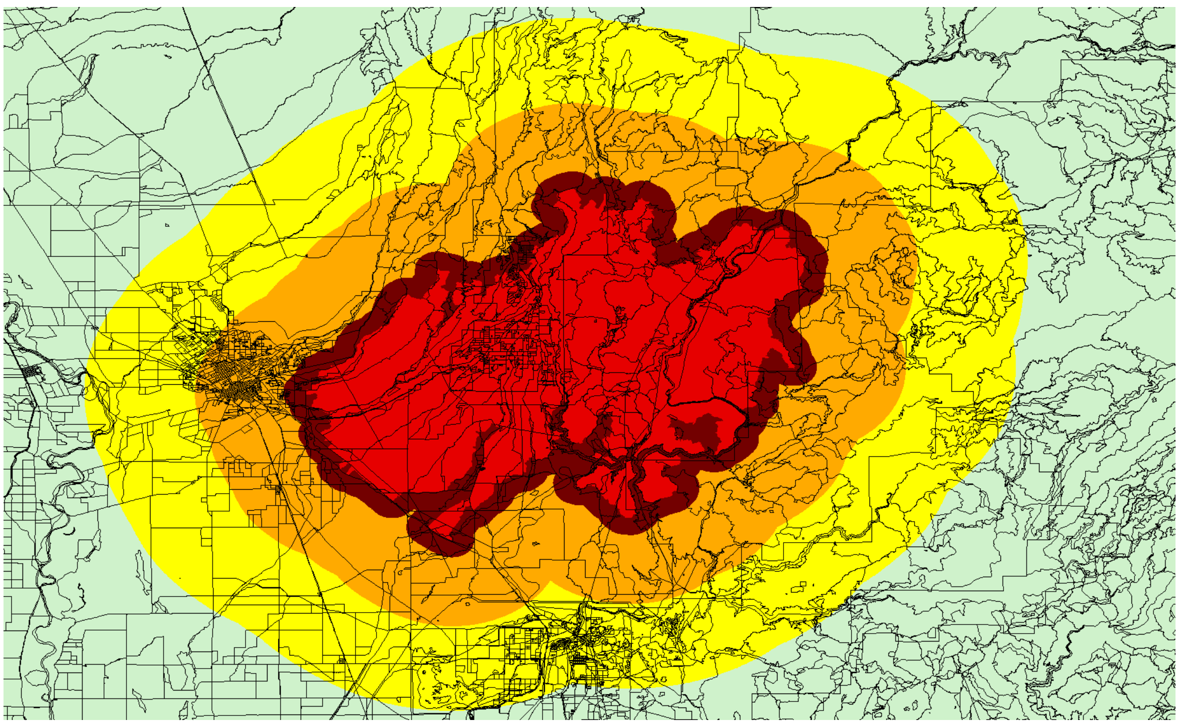


Figure A.2. Treatment and Control Areas in the Camp Fire Analyses

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. Source: U.S. Forest Service Monitoring Trends in Burn Severity (MTBS) database.

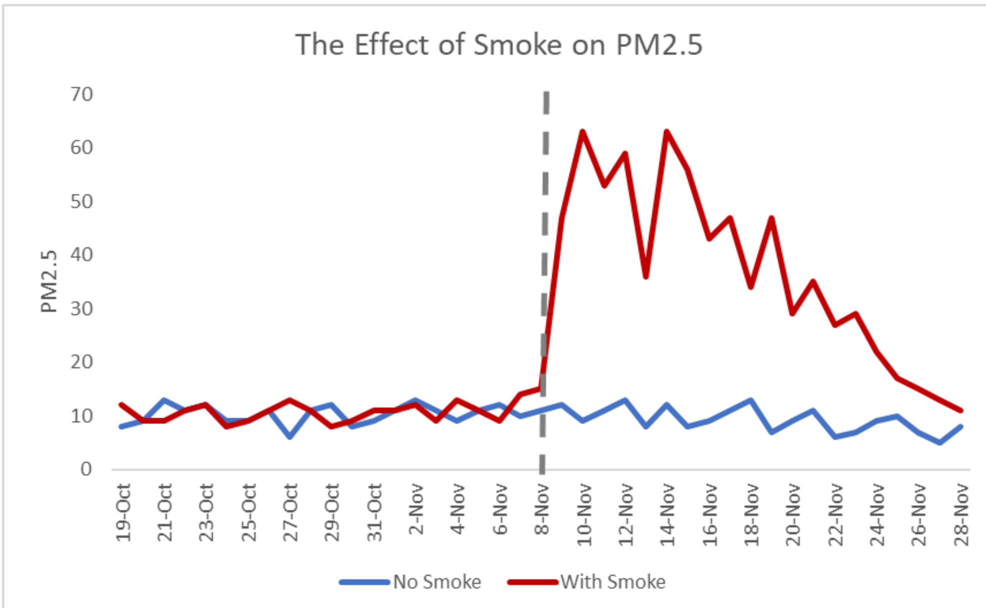


Figure A.3. Wildfire Smoke Elevated PM2.5 After the Camp Fire

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 Camp Fire, between zip codes that experienced smoke, and zip codes without smoke, using the following event study specification:

$$PM2.5_{z,d} = \sum_{\tau=-20}^{20} \beta_\tau * SmokeDay_{z,d+\tau} + \alpha_{z,day-of-year} + \varepsilon_{z,d}. \tag{5}$$

We regress the concentration of ambient fine particulate matter $PM_{2.5}$ in a zip code z and on day d on the smoke exposure in each day within 20 days before and after the Camp Fire. Fixed effects include zip code by day of the year, which isolate year-over-year variation in smoke exposure at the zip code level. Our approach is similar to that of Borgschulte et al. (2022). As is evident, in the aftermath of the Camp Fire, and among zip codes treated by wildfire-related smoke, pollution levels increased sharply, to 60 g/m3. Sources: NOAA's Hazard Mapping System (HMS) and EPA's Air Quality System.

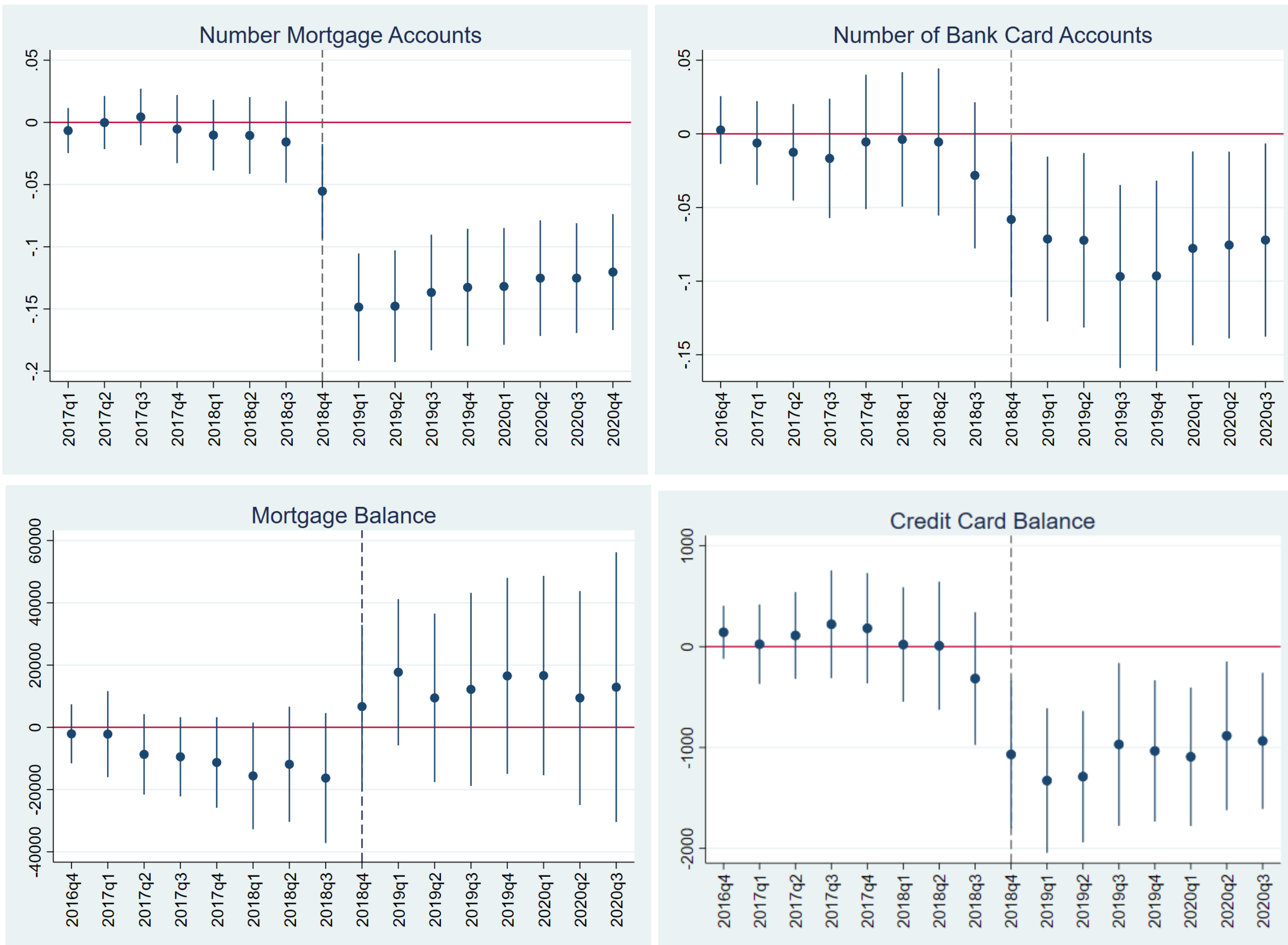


Figure A.4. The Effect of 2018 Camp Fire on the Number of Accounts and Credit Balance - from the FRBNY Consumer Credit Panel/Equifax Data

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 Consumer Credit Panel/Equifax data (CCP).

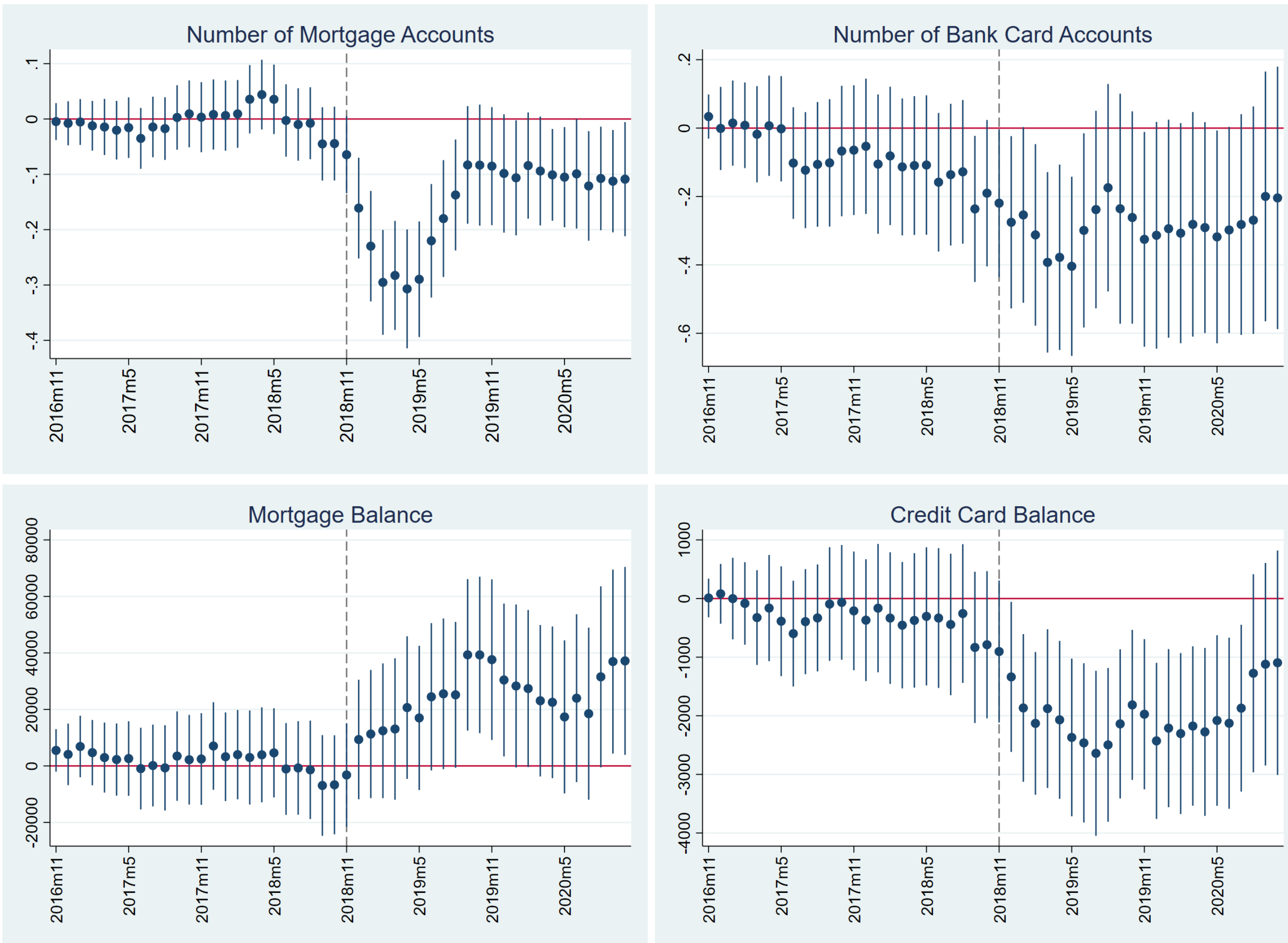


Figure A.5. The Effect of 2018 Camp Fire on Credit Balance and Number of Accounts - From the CRISM

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: Credit Risk Insight Servicing McDash (CRISM).

Table A.1 . List of Extreme Wildfires in the U.S. Between 2016 and 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). Sources: Data on the location and destruction of the fires has been processed by St Denis et al. (2020), using information from the U.S. National Incident Management System/Incident Command System (ICS).

Table A.2 . Descriptive Statistics of Consumers in Fire Burn Areas and Close Proximity

Variable	Fire Zone			Outside Fire Zone		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Total Bank Card Balance	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 four wildfires. The table shows the average among the five different fires (Camp, Carr, Thomas, Central LNU Complex, and LNU Lightning Complex). Sources: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).

Table A.3 . Summary Statistics for Smoke and Pollution

	1 Mean	2 Std. dev.	3 P1	4 Median	5 P3	6 Min	7 Max
Panel A - Camp Fire							
pm25	36.76	17.98	20.95	31.87	31.87	18.22	73.61
pm25 delta	27.09	17.62	12.32	20.81	42.60	6.67	61.81
Stanford Echo Lab measure	57.95	37.74	11.86	35.88	90.41	0	282.97
Panel B - Carr Fire							
pm25	39.98	7.21	33.50	37.49	46.11	30.75	53.02
pm25 delta	13.53	5.79	24.93	28.01	36.48	20.51	44.11
Stanford Echo Lab measure	38.42	21.38	23.36	36.10	53.07	0	115.65
Panel C - Thomas Fire							
pm25	18.28	10.64	10.37	15.26	19.07	5.62	47.31
pm25 delta	8.11	10.64	0.47	2.11	13.04	-1.04	40.59
Stanford Echo Lab measure	23.01	29.66	4.91	11.14	28.30	0	199.11
Panel D - Central LNU Complex							
pm25	16.78	3.01	14.95	16.43	18.41	10.72	28.06
pm25 delta	11.61	2.38	18.41	11.39	12.28	6.15	22.52
Stanford Echo Lab measure	28.32	23.32	12.58	23.27	39.52	0	179.55

Notes: This table provides summary statistics for pollution levels, pollution delta (compared with the same month in the previous three years), and predictions of smoke-$PM_{2.5}$ from the Stanford University Environmental Change and Human Outcomes (ECHO), for each of the four wildfires in our paper in the month that the fire occurs. We explore all zip codes in a radius between 5 to 30 miles from each fire. Sources: Air pollution data were obtained from the EPA's Air Quality System, and the smoke-$PM_{2.5}$ prediction is obtained from the Stanford University Environmental Change and Human Outcomes (ECHO) Lab.

Table A.4 . Effects of Camp Fire-Induced Pollution on Credit Outcomes - Up to 100 Miles

Panel A - 30-50 Miles	1 Mortgage Delinquency	2 Credit Card Delinquency	3 Personal Loan Delinquency	4 Retail/Store Card Delinquency
$Treated \times Post$	0.004*	0.000	0.028***	0.031***
	(0.002)	(0.001)	(0.005)	(0.003)
Time-varying borrower attributes	✓	✓	✓	✓
Borrower FE	+	+	+	+
Q-year FE	+	+	+	+
Observations	19,116	53,891	13,011	17,734
R-squared	0.549	0.793	0.790	0.808
Dependent variable	0.022	0.034	0.072	0.109
Panel B - 50-100 Miles	Mortgage Delinquency	Credit Card Delinquency	Personal Loan Delinquency	Retail/Store Card Delinquency
$Treated \times Post$	0.003	-0.002	0.004	0.002
	(0.008)	(0.002)	(0.007)	(0.014)
Time-varying borrower attributes	✓	✓	✓	✓
Consumer FE	+	+	+	+
Year-qtr FE	+	+	+	+
Observations	322,424	878,749	159,114	245,439
R-squared	0.584	0.792	0.806	0.822
Dependent variable	0.016	0.032	0.076	0.110

Notes: This table shows the IV estimates of the effect of wildfire-related air pollution on credit delinquencies in a difference-in-differences framework. We compare borrowers that were in zip codes exposed to heavy pollution (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 5 $\mu g/m^3$), before and after the Camp Fire. The time frame is 14 months before and after the Camp Fire. We focus on zip codes located 30 to 50 miles from the Camp Fire (Panel A) and 50 to 100 miles from the Camp Fire (Panel B). The time frame is two years before the Camp Fire and 18 months after. Robust standard errors in parentheses (error terms clustered at zip code-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data, and Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP) for credit data.

Table A.5 . Effects of Camp Fire-Induced Pollution on Credit Card Spending and Repayment: Up to 100 Miles

	1	2	3	4
Panel A: 30-50 Miles	Δ Spending	Δ Payment	Δ Balance	Δ Past Due
$Treated \times Post$	698.6**	-481.4	1123.9	0.045
	(301.0)	(400.2)	(693.9)	(0.039)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	99,865	99,865	99,865	99,865
Adjusted R-squared	0.047	0.026	0.470	0.293
Panel B: 50-100 Miles	Δ Spending	Δ Payment	Δ Balance	Δ Past Due
$Treated \times Post$	419.1*	-375.6	782.4	-0.006
	(213.5)	(249.7)	(977.5)	(0.031)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month	+	+	+	+
County by quarter FE	+	+	+	+
Observations	360,442	360,442	360,442	360,442
Adjusted R-squared	0.061	0.043	0.237	0.269

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 30-100 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 (e.g., PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., PM2.5 smaller than 5 $\mu g/m^3$), 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, year-month fixed effects and county by quarter fixed effects. Additional time-varying control variables include refreshed borrower credit score, current credit limit of the credit card account, and utilization rate. Robust standard errors in parentheses (error terms clustered at the county-level): ***p < 0.01, **p < 0.05, and *p < 0.1. Sources: Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data; Federal Reserve Y-14M for credit card data.

Table A.6 . Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Repayment: Different Fires

	1	2	3	4
Panel A: Δ Spending	Camp Fire	Thomas Fire	Carr Fire	Central LNU
$Treated \times Post$	612.0***	398.2	864.0***	141.4
	(53.2)	(576.4)	(396.2)	(294.5)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Month-year FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	645,681	160,516	92,115	381,834
R-squared	0.059	0.100	0.053	0.045
Dependent variable mean	-403.0	-347.3	-245.4	-296.7
Panel B: Δ Payment	Camp Fire	Thomas Fire	Carr Fire	Central LNU
$Treated \times Post$	-562.7**	-280.5	-1636.3***	-258.5
	(281.0)	(406.3)	(118.8)	(292.5)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	645,681	160,516	92,115	381,834
R-squared	0.044	0.051	0.022	0.027
Dependent variable mean	379.1	72.1	124.3	132.9

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 borrowers 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. Sources: Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data; Federal Reserve Y-14M for credit card data.

Table A.7 . 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 × *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, based on year of birth, 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 Consumer Credit Panel/Equifax data (CCP).