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The Effects of Wildfire and Distant Air Pollution on Household Financial Well-Being*

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ABSTRACT

While exposure to wildfire smoke is adverse to human health, little is known about related impacts on household economics. In this paper, we link granular wildfire burn, smoke plume, air pollution, and consumer credit data to estimate the impact of extreme wildfire and related dispersed air pollution effects on consumer financial health. We find material effects including increased credit card and personal loan delinquencies among households distant from the burn perimeter but exposed to high levels of pollution. Further analysis of confidential supervisory data reveals elevated spending and indebtedness among pollution-treated households, which corroborates and explains the delinquency findings. Finally, we present evidence of health spending and work disruption channels of smoke effects. Findings indicate that the adverse effects of extreme wildfires are salient to substantial dispersed populations, including those distant from the fire zone.

JEL Classification: G5, Q54, D12.

Keywords: Wildfires, Air Pollution, Consumer Credit, Financial Distress, Health.

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I. Introduction

Wildfires not only destroy proximate structures and communities, but also spew toxic particulate pollution across distant populations and geographies (Burke et al., 2021). In June 2023, for example, heavy smoke and particulate emissions from prolific Canadian wildfires blanketed 122 million people across much of the Northeast and North Central United States, resulting in some of the most polluted days on record.[1] The tiny particles contained in wildfire smoke are up to 10 times more harmful to human health than those released from car exhaust or other known sources (Aguilera et al., 2021). Through health and work disruption channels, wildfire smoke events could also be highly detrimental to household financial health. However, little is known, and there are few estimates of household economic effects.

In this paper, we provide novel estimates of the effects of wildfire smoke on consumer financial health. 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. In addition to detailed geographic information about 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. Because measured $PM_{2.5}$ could reflect changes in pollution levels due to factors other than wildfire smoke, we also employ estimates of wildfire-attributed $PM_{2.5}$ from a machine learning model developed by Childs et al. (2022) for a 10 km-by-10 km grid across the contiguous US. We utilize detailed consumer-level and loan-level datasets, including the FRBNY Consumer Credit Panel/Equifax Data (CCP); the Equifax Credit Risk Insight Servicing and ICE, McDash

[1] See, "Over 122 million under air quality alerts from Chicago to DC as Canadian wildfire smoke pours into US," Fox Weather, June 28, 2023.

(CRISM) data;[2] and the Federal Reserve Y-14M Data to measure consumer credit outcomes. In addition, we leverage the California Health and Human Services Open Data Portal and the U.S. Census Bureau Quarterly Workforce Indicators (QWI) to investigate the underlying mechanisms of wildfire smoke effects. The combination of comprehensive and granular data provides 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 burn 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 more distant from the wildfire boundary. Those areas do not incur property damage due to the wildfire, but often are affected by wildfire smoke. Due in part to topography 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 exogenous 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 that experienced only 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 over the prior three years. Second, we utilize estimates of wildfire-attributable $PM_{2.5}$ based on an instrumental variable approach. The granularity of our data enables us to include consumer- or credit account-level fixed effects, so as to largely alleviate concerns of omitted variable bias.

[2]CRISM is a match between anonymous credit reports from Equifax and administrative mortgage data from ICE, McDash.

We find statistically significant and economically salient increases in loan delinquencies in the wake of a fire-attributable pollution event. For example, higher levels of wildfire-related air pollution cause credit card and personal loan delinquencies to increase by 3-4 percentage points. To understand these delinquency results, we examine household credit usage, repayment, and balance. Our Y-14M data allow us to directly observe credit card balance and whether an increase in credit card balance is due to an increase in spending and/or a decline in credit card repayment. In the five quarters following the 2018 Camp Fire, for example, among consumers exposed to high levels of wildfire-induced particulate pollution, the combination of additional credit card spending and reduced credit card repayment added about $1,000 per annum to credit card balance. Further analysis indicates that the increase in credit card spending was associated with prime borrowers and borrowers with high credit limits, who likely had greater capacity to spend more on preventive measures to combat wildfire-induced air pollution. By contrast, borrowers with low credit limits did not spend more using their credit cards but repaid less. This finding is consistent with the idea that lower-income borrowers, in the absence of emergency government assistance, have fewer resources to cope with labor market or health effects of major pollution events.

We also seek to better understand the health and labor market mechanisms associated with increased wildfire pollution-related financial distress. We first turn to Google search data to document the association between wildfire-attributable air pollution and health-related concerns and mitigants. We then assess data on health outcomes and find significant adverse effects of the smoke and pollution events on child and adult respiratory disease emergency department visits. Those findings are consistent with broadly reported media accounts of harmful wildfire smoke effects.

The existing literature also indicates productivity declines associated with wildfire smoke. We use information from the U.S. Census Bureau Quarterly Workforce Indicators (QWI) dataset, which covers most workers in the U.S., to show that borrowers exposed to higher levels of wildfire-related air pollution, on average, experienced declines in earnings and employment in the quarters subsequent to the wildfire event. Together, these findings point to both a health-related spending channel and an income channel in explanation of the adverse wildfire smoke and pollution financial effects.

As a comparison, we also estimate direct burn zone impacts of wildfires. Here we contrast financial outcomes among households within the fire perimeter with those for households beyond 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, the adverse household fire treatment effects typically persisted multiple quarters after the fire. As above, we use information from the Y-14M consumer database to study credit card spending, repayment, and monthly balance in the wake of 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.

Insurance often plays an important role in offsetting wildfire expenses among homeowners (Boomhower et al., 2023). In California, numerous private insurers have withdrawn from the market and canceled homeowner policies in high wildfire risk areas.[3] However, the State of California

[3] This is a broader phenomenon that is relevant for other natural disaster events, and in general, insurance companies are exiting high-risk areas (Sastry, 2021; Ge et al., 2025; Oh et al., 2022; Keys and Mulder, 2024).

has made basic fire coverage available via the California FAIR Plan (Biswas et al., 2023).[4] Among homeowners, our finding of limited near-term adverse household financial impact of wildfire (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 the use of their own limited resources to cope with adverse fire effects, including work disruption as well as event-related health expenses. Further, the adverse smoke and pollution effects of distant wildfires typically are not covered by insurance, making the smoke effects as documented in this paper especially prominent.

A few recent papers, including Issler et al. (2020), McConnell et al. (2021), Cookson et al. (2023) and Biswas et al. (2023), examine the effects of wildfires on burn zone housing and consumer outcomes.[5] There are also a limited number of papers that evaluate the effect of air pollution on housing outcomes.[6] Ours is the first paper to employ detailed and granular supervisory, extreme wildfire, air quality, and particulate pollution data to estimate both the household financial burn zone and related disbursed air pollution effects of extreme wildfire events. We employ those estimates to compute aggregate economic costs of extreme wildfire events. Per above, our estimation results indicate that both dispersed wildfire-attributed pollution and proximate burn zone

[4]The California FAIR Plan provides limited, 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.

[5]Compared with the literature on the effects of wildfires, the literature on effects of other natural disasters is more extensive. Existing research finds that floods and hurricanes lead to temporary increases in delinquency rates (Kousky et al., 2020; Billings et al., 2022; Nguyen et al., 2022; Keys and Mulder, 2020).

[6]Amini et al. (2022) analyze the causal effect of air pollution on Iran's housing market by exploring 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%.

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 slightly smaller increase in the likelihood of credit card and personal loan delinquencies among those exposed to fire-related particulate emissions and pollution events, compared with estimated increase in delinquencies among burn zone households. The 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 to credit card debt.

The geographic incidence of major smoke and air pollution events became significantly more pronounced in the wake of major wildfire events in North America and Europe during the summer of 2023. According to a 2024 report by First Street, in an elevated pollution year, poor air quality days in some areas of California are expected to increase from two months under current environmental conditions to in excess of three months over the next 30 years.[7] Failure to account for the effects of broadly diffused and growing consequential fire emissions yields an incomplete economic rendering both of these extreme natural disasters and related costs and benefits of risk mitigation efforts.

Our paper also provides evidence of financial fragility of US households in the wake of unexpected expenses. Survey evidence suggests that many households are unable to cope with relatively modest income/expense shocks (Hasler et al., 2018). In fact, the 2023 Survey on Household Economics and Decisionmaking (SHED) showed that 37 percent of adults would have difficulty

[7] For more information, see https://firststreet.org/research-library/atrocious-air.

covering a hypothetical expense of $400. Lusardi et al. (2011) report that one-quarter of Americans would not be able to come up with $2,000 in 30 days. Our findings show that US households are financially vulnerable to similar unanticipated natural disaster-related shocks. Related expenses are shown to push them into credit delinquency.

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 wildfire data compiled by the US Department of Homeland Security National Incident Management System/Incident Command System (ICS) and processed by St. Denis et al. (2023). Data include fire event information including the number of structures destroyed, acres burned, injuries and deaths.[8] We use the most recent version of data for 2016 - 2020. To identify the wildfire burn perimeters, we use the MTBS identifier in the ICS-209-PLUS Incident Summary in St. Denis et al. (2023) to 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 blocks/tracts/zip codes included in the fire burn perimeter and beyond.

The analysis focuses largely on the 2018 Camp Fire, the most destructive wildfire event of the 2016 - 2020 pre-COVID-19 period. We also include in the analysis other extreme wildfires that

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

destroyed more than 1,000 structures. Those wildfires, like the vast majority of extreme wildfires in the US to date, occurred in California. Appendix Table A.1 provides a list of extreme US wildfires during 2016 - 2020 and the number of structures destroyed. We further limit the analysis to fires that occurred at least 6 quarters pre-COVID-19 to ensure that pandemic effects do not contaminate our estimates of household credit outcomes. Accordingly, our sample comprises four extreme wildfires in California during that period, 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 Appendix Figure A.2. Appendix 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).[9] The HMS uses observations from the Geostationary Operational Environmental Satellite, which produces imagery at a 1-km resolution for visual bands and a 2-km resolution for infrared bands to identify fire and smoke emissions over the contiguous United States (Ruminski et al., 2006). Smoke analysts process the satellite data to draw geo-referenced polygons that represent the spatial 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

[9]These data come from an operational group of NOAA experts who rely on satellite images to identify the location and the movements of every wildfire smoke plume in the U.S.

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 (Childs et al., 2022), which are computed 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 wildfire-attributable smoke $PM_{2.5}$ over a 10 km-by-10 km grid for the contiguous U.S. from 2006 to 2020.[10] Appendix Table A.3 provides summary statistics for smoke and pollution for our sampled areas. Figure 1 shows the smoke-$PM_{2.5}$ predictions by Stanford ECHO Lab estimates in the two weeks after the outbreak of the Camp Fire. We can see a clear, sharp increase in wildfire smoke pollution during the two weeks after the Camp Fire. During that period, many zip codes 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 $\mu g/m^3$.

[10] 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.

D. Credit and Consumer Spending Data

We measure household credit outcomes using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax anonymous credit file (CCP). The CCP is a nationally representative 5% random sample of individuals with a credit report.[11] The panel provides detailed credit-report data for individuals and households at quarterly frequency 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.[12]

In order to contrast outcomes across housing tenure status (homeowners vs renters), we turn to the Equifax Credit Risk Insight Servicing and ICE, McDash (CRISM) data. CRISM is an anonymous credit file match of Equifax's full population of consumer credit reports to the ICE, McDash loan level mortgage dataset.[13] 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 case of the CCP.

To supplement the CCP, we obtain anonymous account-level information on consumer credit card activity from the Federal Reserve Capital Assessments and Stress Testing Y-14M data collection. In addition to its higher frequency, the monthly Y-14M data have the important advantage of detailed credit card spending, repayment, and balance information for the same accounts. 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

[11] 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.

[12] For more information, see Lee and van der Klaauw (2010).

[13] 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 ICE, McDash dataset to a particular consumer's tradeline in Equifax.

the 9-digit zip code.[14] The data also contain credit performance information, including an account past due indicator.[15] 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 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 its 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 robustness purposes, we also evaluate the effects of smoke and pollution at distances of 30 to 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 during the two 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 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 10 $\mu g/m^3$; and lightly polluted zip codes defined as those with average daily $PM_{2.5}$ less than 10 $\mu g/m^3$.[16] Our treatment group comprises the heavily polluted zip codes; our control group includes the lightly polluted zip codes; and the

[14] Some accounts include only the 5-digit zip code.

[15] See Agarwal et al. (2020) for more information.

[16] 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."

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:

$$y_{i,t} = \gamma * Pollution_z * Afterfire_t + x_{i,t}'\Gamma + \tau_t + \zeta_i + \varepsilon_{i,t}, \tag{1}$$

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

$$y_{i,t} = \gamma * \Delta PM2.5_z * Afterfire_t + x_{i,t}'\Gamma + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{2}$$

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 $PM_{2.5}$ may reflect factors beyond wildfire-related smoke, notably including economic activity in the study area, making our shock 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 Appendix Figure A.3, we demonstrate how days of wildfire smoke caused $PM_{2.5}$ to increase significantly in the aftermath of the fire. As is evident, in the wake 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 Appendix Figure A.3). As the Stanford ECHO Lab estimates are likely to more accurately attribute $PM_{2.5}$ to wildfire smoke, we use their estimates of wildfire smoke-related $PM_{2.5}$ in the second stage of our IV regression:

$$y_{i,t} = \gamma * \widehat{PM2.5}_z * Afterfire_t + x_{i,t}'\Gamma + \tau_t + \zeta_i + \varepsilon_{i,t}. \tag{3}$$

Here the $\widehat{PM2.5}_z$ are the zip code-level daily estimates obtained from the Stanford ECHO Lab aggregated to monthly frequency.[17] In order to evaluate how wildfire-induced air pollution dissipates over time, we also run event-study type of regressions in a similar difference-in-differences setting.

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

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

June 2023 resulted in dangerous and unhealthy air for tens of millions of households in the North Central and Northeast United States. The Centers for Disease Control and Prevention estimated that emergency department visits for asthma were 17% higher than expected during 19 days of wildfire smoke that occurred during the Canadian wildfires (McArdle, 2023).[18]

B.1. Baseline Results on Credit Delinquency

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 10 $\mu g/m^3$, 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 for the analysis are the 14 months before and after the Camp Fire (prior to the start of the COVID-19 pandemic). Column 1 in Panel A shows no significant increase in the likelihood of mortgage delinquencies for the treatment group in the wake of exposure to high levels of wildfire-attributed air pollution. However, Columns 2 and 3 show that exposure to high levels of pollution results in increases in credit card and personal loan delinquencies. The estimated effects on credit card and personal loan delinquencies are sizable: Borrowers exposed to higher levels of wildfire-related air pollution, on average, experienced an increase in credit card and personal loan delinquencies of 2.1 and 3.5 percentage points per annum, 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. For example, higher levels of wildfire-

[18] Maldarelli et al. (2024) show adverse cardiopulmonary disease events in eastern US communities were associated with exposure to remote wildfire smoke in the wake of the Canadian wildfires.

related air pollution cause credit card and personal loan delinquencies to increase by 3-4 percentage points (40-50 percent). These results are statistically and economically significant. Also, the IV approach shows that higher levels of wildfire attributable air pollution result in a small (10 percent) but statistically significant increase in mortgage delinquency. Appendix Table A.3 contains summary statistics on smoke and pollution for sampled areas. In Figure 2, we plot the time-varying effects of wildfire-induced air pollution on credit delinquency. To make the comparison more precise, we undertook to propensity score match (based on income, race, and homeownership characteristics from the Census) zip codes in lightly polluted areas and more heavily polluted areas. In the initial quarter following the Camp Fire, we see a marked increase in credit card and personal loan delinquency rate. For the credit card delinquency rate, the estimated effect remains elevated two years after the Camp Fire. For the personal loan delinquency rate, the estimated effect remains elevated in the fourth quarter but tends to dissipate over time.

B.2. Credit Card Usage and Repayment

We use Federal Reserve Y-14M data to assess borrowers' credit card usage and repayment activity and to better understand the mechanisms behind the wildfire smoke related trends in delinquency. Table 2 shows the effects of Camp Fire-induced air pollution on credit card spending and repayment. 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, and account balance. 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 over $750 on an annual basis relative to those exposed to lower levels of wildfire-induced air pollution. Also, repayment of credit card debt was significantly less among treated households. As a result, treated households accumulated roughly $1150 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 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 are estimated to have accumulated roughly $1000 more in annualized credit card debt. As discussed above, the regression model's substantial controls include highly granular fixed effects and time-varying borrower attributes (including time-varying borrower credit scores and current credit limit of the accounts). We also test different $PM_{2.5}$ cutoffs in constructing the control and treatment groups and find results to be highly robust.

In Figure 3, 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 increase 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 among those who were exposed to heavy air pollution.

Table 3 reports on heterogeneity in smoke effects among population stratified by credit score. The increase in credit card spending is found largely among borrowers with high credit scores (greater than 780) and high credit limits (higher than $5,000). Those borrowers are likely higher income borrowers and thus have the capacity to spend more on preventive measures to combat air pollution induced by wildfire. For borrowers with low credit score (below 660), we see reductions in credit card spending in the wake of a wildfire smoke-induced air pollution event. Further, borrowers with low credit limits (below $1,000) did not spend more using their credit cards but repaid less. This finding is consistent with the idea that lower-income borrowers, in the absence of emergency government assistance, have fewer resources to cope with labor market or health effects of major pollution events.

In Appendix Table A.7, we compare our IV wildfire-induced pollution estimates across different extreme wildfires. While results vary across wildfires, they are qualitatively consistent in indicating that consumers exposed to relatively heavy air pollution spend more and repay less, compared to those in areas exposed to low or no pollution.

B.3. Effects of Distant Diffusion of Wildfire Smoke

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 to 100 miles from the fire perimeter, which captures large and populated areas around Sacramento. The results are robust to those presented in Table 1. Further, we find a small but statistically and economically elevated rate of credit card delinquency (Column 2 of Table A.4). On average, borrowers exposed to higher levels of wildfire-related air pollution experienced an increase in credit card delinquency of 0.7 percentage points, relative to those exposed to lower levels of wildfire-induced air pollution.

In Appendix Table A.5, we assess the robustness of credit card spending and repayment results to more distant diffusion of wildfire-related smoke and pollution. Similar to above, we study credit card accounts of borrowers who live 30 to 100 miles from the Camp Fire boundary. 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 30-100 miles from the fire perimeter. Even at that distance from the wildfire, repayments were less, and borrowers exposed to wildfire smoke accumulated significantly more credit card balance over time.

Finally, we extend the geographic purview of the analysis to include borrowers in the entirety of Northern and Central California. As shown in Figure 1, heavy Camp Fire smoke traveled substantial distance to blanket the entire San Francisco Bay Area. In the figure, we use darker colors to indicate areas exposed to more smoke. To make the comparison more precise, we undertook to propensity score match (based on income, race, and homeownership characteristics from the Census) zip codes in lightly polluted areas and more heavily polluted areas. Then we ran a DID analysis similar to that specified in equation 3 using credit card accounts in the propensity score matched zip codes. Appendix Table A.6 shows credit card spending and repayment results consistent with those reported above – borrowers in heavily polluted areas were characterized by more spending, less repayment, and higher balance compared to those in less polluted areas.

*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), Qiu et al. (2024)). 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). In fact, a study released by the CDC finds that "(e)mergency department visits for asthma were 17% higher than expected during 19 days of wildfire smoke" (McArdle, 2023). Therefore, when it comes to personal finance, 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.

Given the above discussion, we provide below corroborating evidence of the effects of wildfire-related smoke and particulate air pollution on health outcomes. We start by using Google search data to document the association between wildfire-attributable smoke and air pollution and respiratory concerns and mitigants. Figure 4 shows marked increases in Google Trends internet search for air purifiers as well as elevated concerns regarding smoke 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 the number of emergency department visits for children and the 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 for the analysis is 4 months prior to and after the Camp Fire.

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. (2024).[19] That study uses detailed Medicare data to show that wildfire smoke increases both hospital admissions and outpatient ER visits.[20]

Wildfire-related smoke and pollution may also affect household finances via an employment

[19] Lopez et al. (2024) also show an increase in asthma cases and unprofitable emergency room visits, as a response to an increase in wildfire smoke pollution, which they showed is associated with significantly higher healthcare municipal borrowing costs.

[20] 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. See https://hcup-us.ahrq.gov/reports/ataglance/HCUPAnalysisCA2018Wildfires.pdf.

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 jobs 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.[21] Similarly, Addoum et al. (2023) report on business loss in the immediate aftermath of a wildfire-related pollution event.

In Table 5, we use the same IV approach to explore the effect of wildfire-induced pollution on labor market outcomes. Our primary labor market measures are obtained from the U.S. Census Bureau Quarterly Workforce Indicators (QWI) dataset, which covers most workers in the U.S. Columns 1 and 2 in Table 5 indicate that borrowers exposed to higher levels of wildfire-related air pollution, on average, experienced a decline in earnings, of 0.7% and 2% among current and new employees, respectively. This is compared to an average log earnings of 8.3 for current employees and 7.8 for new hires. Column 3 shows that borrowers exposed to higher levels of wildfire-related air pollution experienced a decline in overall employment of 4.5%, compared to an average log employment in a quarter of 10.9. The results are inline with Borgschulte et al. (2022), described above, who study the effect of wildfire-induced air pollution on the labor market for the entire U.S. We find a larger effect, as we focus on areas that are close to the fire (between 5-30 miles from the fire), and on a few quarters after the most destructive fire in the U.S.[22]

[21] Adhvaryu et al. (2022) 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.

[22] Cvijanovic et al. (2024) also explored the effect of wildfire-smoke pollution on the labor market and find negative effects of wildfire-smoke exposure on worker productivity. Meyer and Pagel (2024) show that changes in air pollution affect productivity in

The above documented adverse health and employment effects of wildfire-related smoke and pollution suggest numerous channels by which air pollution events may affect household spending, indebtedness, and financial distress. Future work could seek to further hone those links using more detailed and granular health outcome and employment data.

IV. Wildfire Smoke vs. Wildfire Burn Effects

Below we estimate the household financial effects of extreme wildfire events among households residing in the fire zone and compare those values to estimates of wildfire-attributable dispersed smoke and pollution events among households living beyond the fire zone. To do this, we employ the same household financial datasets and outcome terms as analyzed above for an identical set of extreme wildfire events and timeframes. The combination of those estimates enables a broader and more complete discussion of household 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 counterintuitive 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.

cognitively demanding tasks, such as trading.

However, compensation of household economic loss via wildfire insurance 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:

$$y_{i,t} = \beta * Fire_{b,t} * Post_t + x_{i,t}'\Gamma + \tau_t + \zeta_i + \varepsilon_{it}, \tag{4}$$

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 a census block which 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 zero prior to the event. $x_{i,t}$ are time-varying borrower characteristics. 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 data is that we observe not only 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 allows 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 smoke effects and separately identify burn zone fire effects.

B. ***Estimated Wildfire Effects***

Table 6 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 comprises 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 1-3 include mortgage delinquency, credit card delinquency, and personal loan delinquency, respectively. Results indicate that the Camp Fire resulted in statistically significant increases in mortgage, credit card, and personal loan delinquencies. For example, Column 2 shows that consumers living in the burn zone experienced an additional 3.1 percentage point 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 represents a 42 percent increase given an average credit card delinquency rate of about 7.3 percentage points in our sample. The impact of wildfire burn on personal loan delinquency is also significant – a 60 percent increase as reported in column 3. The mortgage delinquency result reported in column 1 is quite large – 2.2 percentage points or 170 percent increase in mortgage delinquency for consumers living in the burn zone. All regressions include year-quarter and consumer fixed effects.

Table 6 provides estimates of the average treatment effects of the Camp Fire on consumer financial distress over the eight quarters following the fire. In Figure 5, we apply our difference-in-differences framework to estimate quarterly 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. Appendix Table A.7 provides delinquency rate estimates for the Carr, Thomas, and LNU Fires. As expected, the more severe Camp Fire had a larger effect on delinquency rates compared to the other three fires.

In Table 7, 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).

In Figure 6, 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 shown in Tables 6 and 7 appears puzzling. A possible explanation is 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 payouts were more likely to become delinquent in their payments in the wake of wildfire-related increased credit card 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.[23] 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 8 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 suggests 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

[23] In the 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.

their elevated credit card debt and were more likely to fall into delinquency.

Unfortunately, insurance claims payout data providing direct evidence of related payouts is not available from the California Department of Insurance. However, 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 payout argument is supported by corroborating analyses displayed in Appendix Figures A.4 and A.5. Specifically, Appendix Figure A.4 shows that among borrowers who remained in the fire zone subsequent to the Camp Fire, both the number of credit card accounts and credit card balance declined significantly in the aftermath of the fire.[24] In Appendix Figure A.5, findings from CRISM data show the decline in credit card accounts and balance was significantly larger among mortgage borrowers residing in the fire zone.[25]

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 3 and Figure 6 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 immediately following the wildfire), whereas wildfire damage in the fire zone caused more spending but also increased repayment and hence a decline in indebtedness (- $5,000 at peak in the quarters following 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 slightly smaller than those stemming directly from the wildfire itself. For example, distant wildfire-attributable emissions and particulate pollution led to an increase in delinquencies of credit card, personal loan, and mortgages

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

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

of 43, 49, and 4 percent, respectively, whereas the Camp Fire burn resulted in an average 42, 64 and 170 percent increase, respectively, in credit card, personal loan, and mortgage delinquencies. 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.

V. Conclusions

Despite the growing incidence, severity, and geography of large 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 due to substantial, far flung, and lingering wildfire-related smoke and particulate emissions. The detrimental effects of wildfire pollution events on household finance may occur via health and employment disruption channels. In this paper, we provide detailed, granular estimates of proximate wildfire burn vs widely disbursed smoke and particulate pollution effects on a broad array of household financial and health indicators. We employ those estimates to compute aggregate economic costs of extreme wildfire events. The analysis derives from the combination of highly-articulated supervisory and other datasets on extreme wildfires, wildfire-induced smoke, air pollution, and consumer financial and health outcomes.

Our analysis provides new estimates of the causal concentration-response relationship between wildfire-attributable air pollution and household financial outcomes. Exposure to heavy pollution results in higher delinquency rates on mortgages, credit cards, and personal loans. 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. Findings further indicate the importance of health-related spending and income channels to consumer pollution-related financial outcomes.

We also estimate the household financial effects of extreme wildfire events among households residing in the fire zone and compare estimates to those associated with wildfire-attributable dispersed smoke and pollution events. The estimated effects of wildfire-induced pollution on household credit usage and credit performance are slightly smaller 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.[26]

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 credit card delinquency of 3 percentage points compared to an average level of 7 percentage points (a 45 percent increase). 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

[26]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 were exposed to heavy Camp Fire 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.

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. Note, however, that our findings rely on assessment of notable extreme wildfire events in California. Future research should gather data so as to directly estimate and assess the external validity of California-based findings to severe wildfire and related smoke and pollution events as recently evidenced in eastern Canada and southern Europe.

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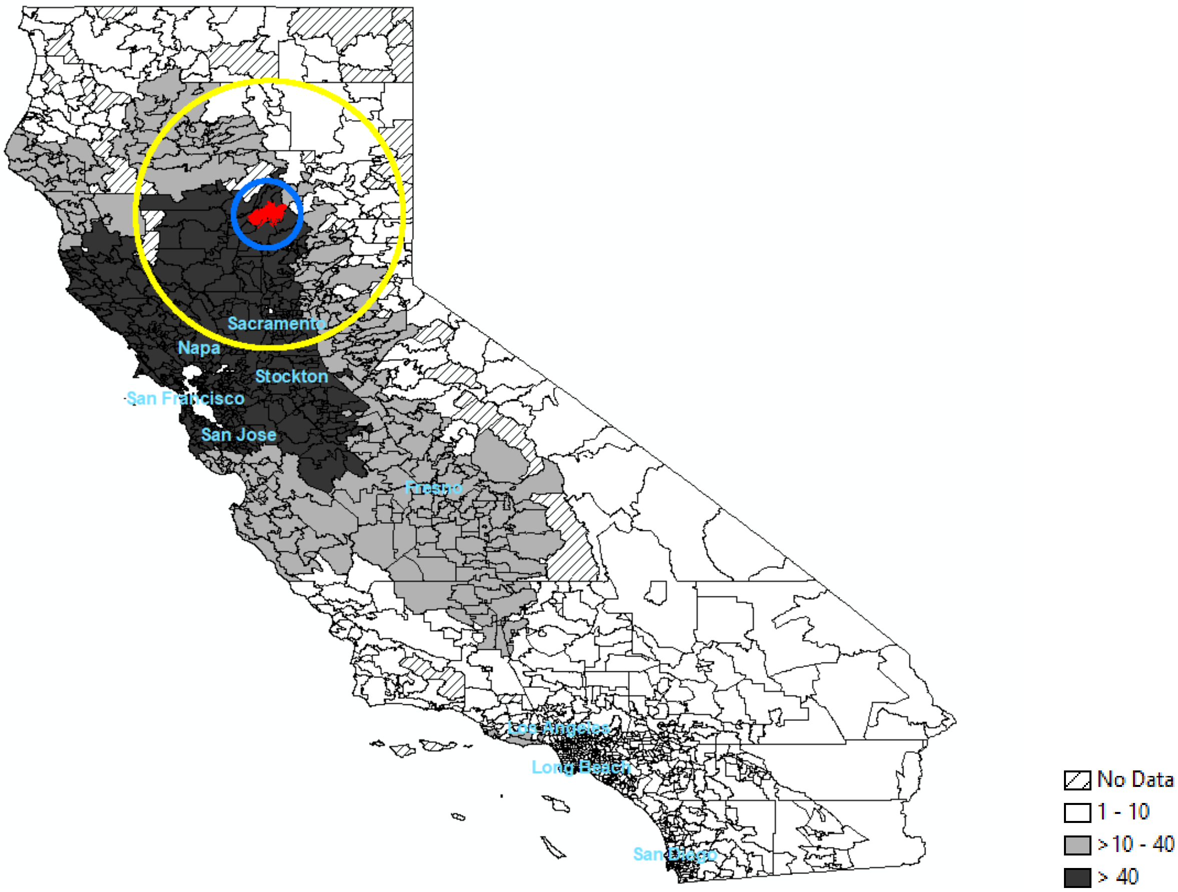


Figure 1. Air Pollution Measured by $PM_{2.5}$ from the Camp Fire

Notes: This figure shows the average $PM_{2.5}$ estimates in the two weeks after the outbreak of the Camp Fire, produced by the Stanford ECHO Lab using a machine learning model to ascribe $PM_{2.5}$ particle matters to the wildfire. The numbers are in $\mu g/m^3$. The red area is the Camp Fire footprint. The blue circle is a radius of 30 miles from the fire and the yellow circle indicates 100 miles from the fire. The border lines on the map are zip codes. Sources: Stanford University Environmental Change and Human Outcomes (ECHO) Lab and Childs et al. (2022).

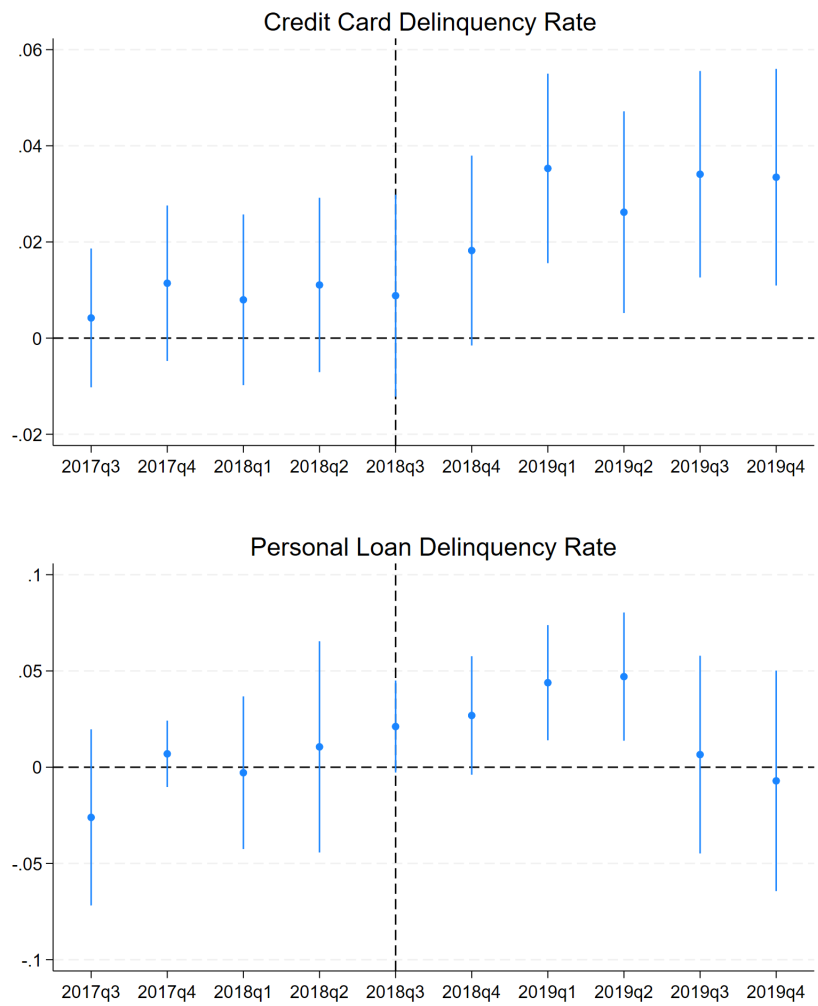
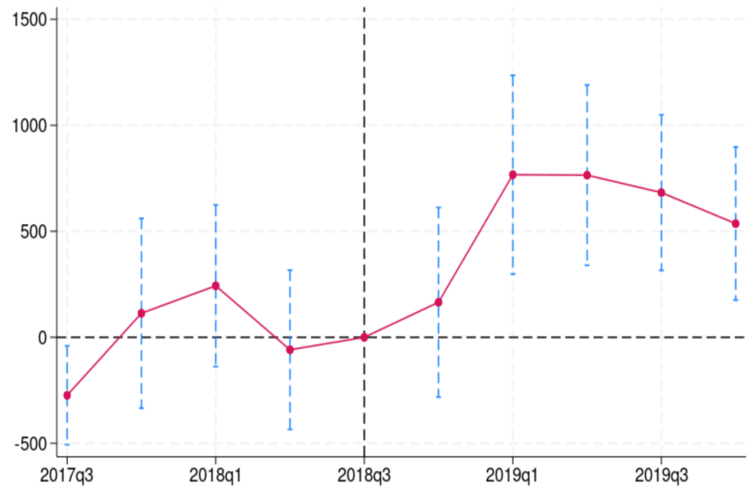
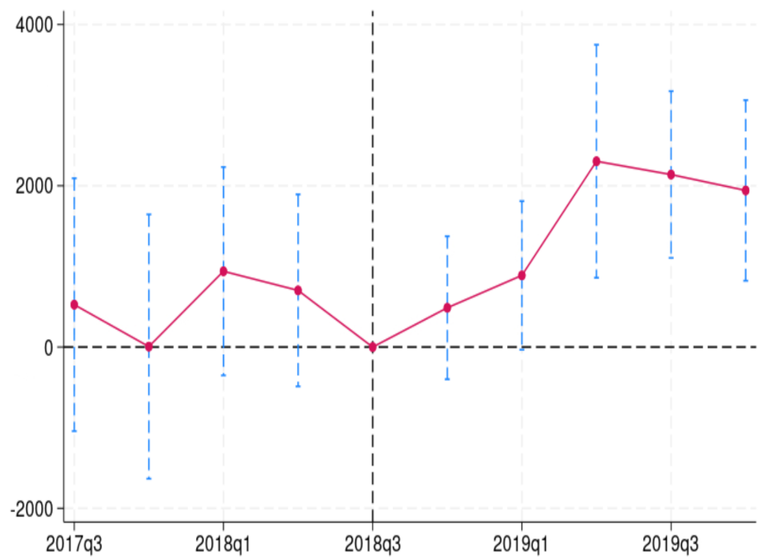


Figure 2. Effects of Camp Fire-Induced Air Pollution on Household Financial Distress

Notes: This figure shows the temporal pattern of the estimated effect of Camp Fire-induced air pollution on consumer credit delinquency rates 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 (PM2.5 greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (PM2.5 less than 10 $\mu g/m^3$), before and after the Camp Fire. To make the comparison more precise, we undertook propensity score match (based on income, race, and homeownership characteristics from the Census) zip codes in lightly polluted areas and more heavily polluted areas. We include consumer fixed effects and year-month fixed effects. Additional time-varying control variable includes credit score. Sources: Air pollution data are from the EPA's Air Quality System and Stanford University Environmental Change and Human Outcomes (ECHO) Lab, and Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).



Panel A Credit Card Spending



Panel B Credit Card Balance

Figure 3. 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 ($PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution ($PM_{2.5}$ less than 10 $\mu g/m^3$), 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, etc. 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.

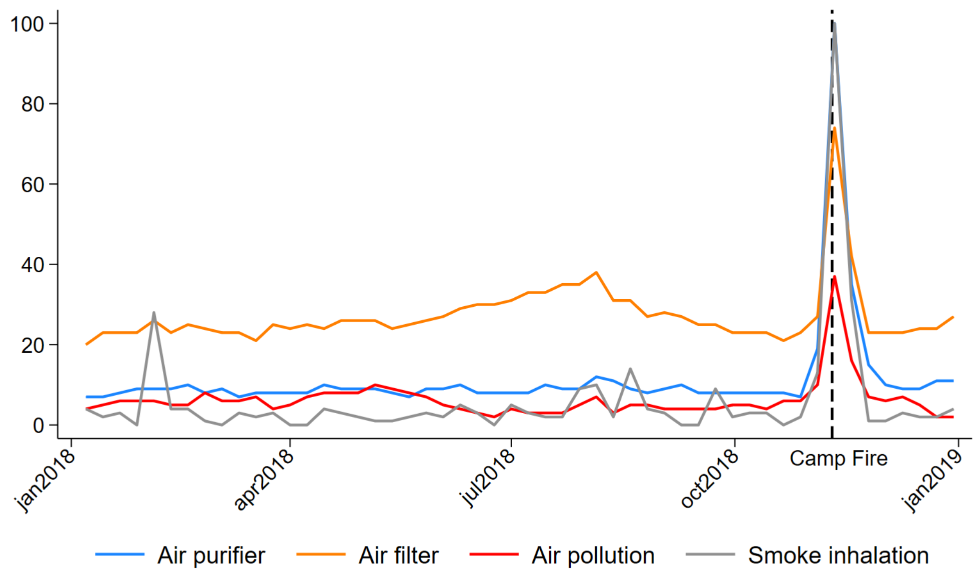
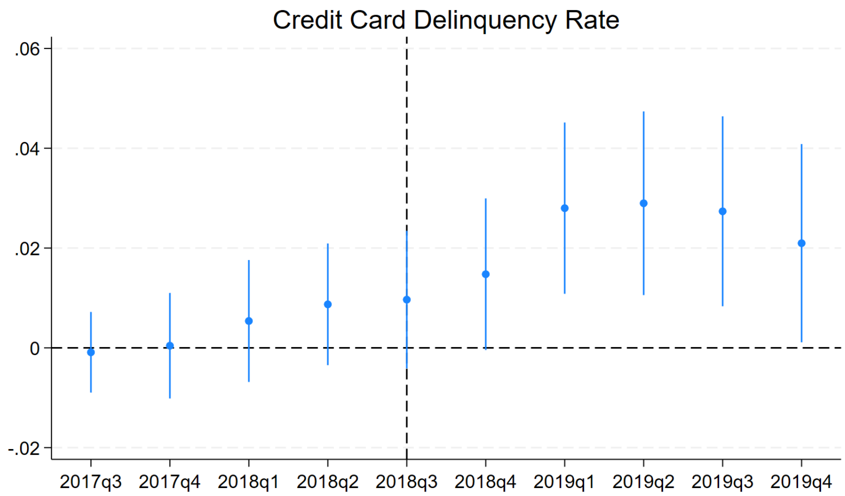


Figure 4. Air Pollution Related Search Queries in the Period Around the Camp Fire

Notes: This figure shows the temporal pattern in search query in California in the period around the Camp Fire, for the indicators of "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.

Panel A



Panel B

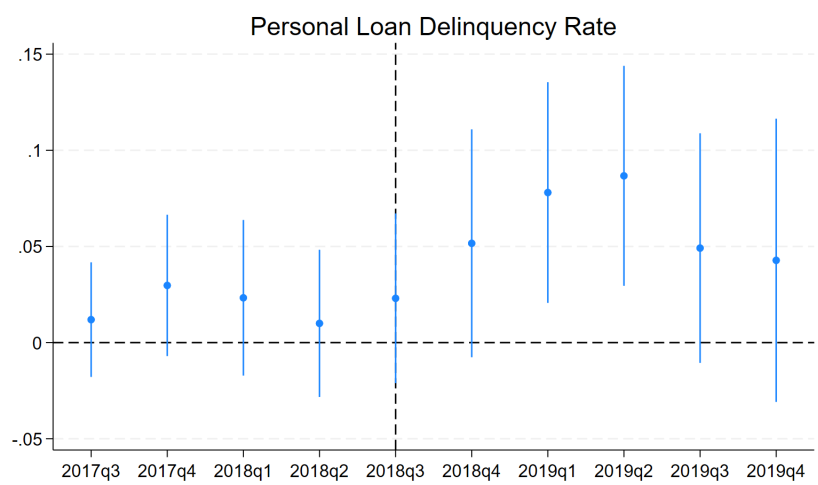
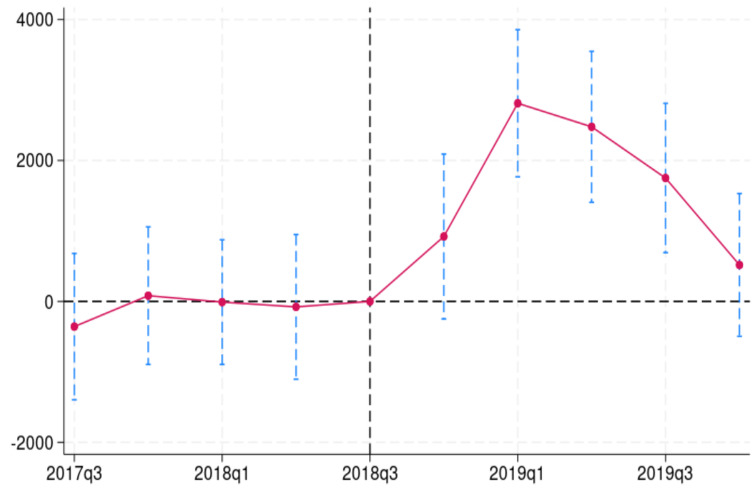
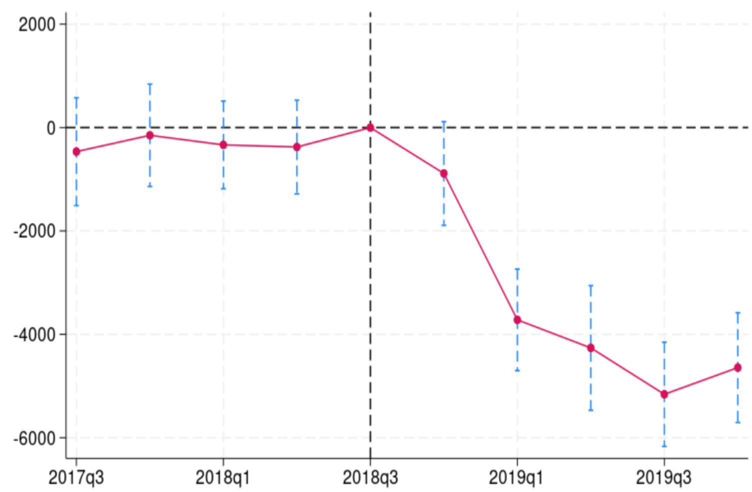


Figure 5. Effects of the Camp Fire on Household Financial Distress

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 year-quarter 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 6. 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
$Treated \times Post$	0.000	0.021**	0.035***
	(0.006)	(0.010)	(0.010)
Time-varying borrower attributes	✓	✓	✓
Consumer FE	+	+	+
Year-qtr FE	+	+	+
Observations	60,668	165,832	38,061
R-squared	0.541	0.689	0.758
Dep. var. mean	0.021	0.072	0.078
Panel B	Mortgage delinquency	Credit card delinquency	Personal loan delinquency
$Treated \times Post$	0.003*	0.028**	0.037***
	(0.001)	(0.013)	(0.007)
Time-varying borrower attributes	✓	✓	✓
Consumer FE	+	+	+
Year-qtr	+	+	+
Observations	43,093	166,111	38,223
R-squared	0.489	0.748	0.730
Dep. var. mean	0.025	0.065	0.076

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., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ 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
Panel A	Δ Spending	Δ Repayment	Δ Balance
$Treated \times Post$	774.7***	-787.3***	1157.2***
	(48.3)	(82.4)	(80.8)
Time-varying borrower attributes	✓	✓	✓
Account FE	+	+	+
Year-month FE	+	+	+
County by quarter FE	+	+	+
Observations	727,110	727,110	727,110
Adjusted R-squared	0.078	0.047	0.447
Dep. var. mean	-249.7	216.2	1351.2
Panel B: IV	Δ Spending	Δ Repayment	Δ Balance
$Treated \times Post$	548.8***	-629.5**	1001.9***
	(163.9)	(263.2)	(243.9)
Time-varying borrower attributes	✓	✓	✓
Account FE	+	+	+
Year-Month	+	+	+
County by quarter FE	+	+	+
Observations	727,110	727,110	727,110
Adjusted R-squared	0.080	0.048	0.447
Dep. var. mean	-249.7	216.2	1351.2

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, 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 that were in zip codes exposed to heavy pollution (e.g., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ smaller than 10 $\mu g/m^3$), before and after the Camp Fire (we have tested different $PM_{2.5}$ cutoffs and found results to be highly robust). The time frame of the analysis is 14 months prior to and 14 months 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, etc. 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 ($) $\leq 1,000$	4 Credit Limit ($) $> 5,000$
$Treated \times Post$	-250.0***	652.0**	22.5	1,057.2**
	(40.1)	(239.1)	(66.9)	(401.8)
Time-varying borr. attri.	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	140,073	211,705	71,584	332,276
Adjusted R-squared	0.126	0.138	0.125	0.089
Panel B: Δ Repayment	Credit Score ≤ 660	Credit Score > 780	Credit Limit ($) $\leq 1,000$	Credit Limit ($) $> 5,000$
$Treated \times Post$	-424.0	-505.7	-181.0*	-995.8**
	(230.2)	(325.8)	(80.1)	(373.7)
Time-varying borr. attri.	✓	✓	✓	✓
Account FE	+	+	+	+
Year-month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	140,073	211,705	71,584	332,276
Adjusted R-squared	0.088	0.067	0.126	0.049

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., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ 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. Year-over-year change (Δ) in spending and payment are annualized dollar amounts. Time-varying borrower attributes include current credit score, current credit limit, etc. 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 Asthma ED Visits	3 Emergency Visits - Kids	4 Asthma ED Visits
$Treated \times Post$	3,149*	1,153*		
	(1,068)	(689.1)		
$DeltaTreated \times Post$			1,298*	1,153*
			(733.2)	(689.1)
County FE	+	+	+	+
Year-month FE	+	+	+	+
Observations	264	212	228	220
R-squared	0.753	0.15	0.536	0.432
Dep. var. 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 75th 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 Camp Fire-Induced Pollution on Earnings and Employment

IV Estimates	1 Log Earning	2 Log Earning (new hires)	3 Log Employment
Treated × *Post*	-0.007**	-0.020*	-0.045***
	(0.002)	(0.010)	(0.005)
County FE	+	+	+
Year FE	+	+	+
Observations	83,735	83,735	83,735
Adjusted R-squared	0.831	0.871	0.849

Notes: This table shows IV estimates of the effect of wildfire-related air pollution on earnings and employment, in a difference-in-differences framework. 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 75th 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 14 months before and after each wildfire, depending on specific wildfire. We include account fixed effects and year fixed effects. Additional time-varying control variables include refreshed borrower credit score and age. Column (1) measures the average monthly earnings from full quarter employment. Column (2) measures the average monthly earnings for the new hires in the last quarter. Column (3) counts the end-of-quarter employment. 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 and the U.S. Census Bureau Quarterly Workforce Indicators (QWI) dataset.

Table 6. Effects of the Camp Fire on Consumer Financial Distress

	1 Mortgage delinquency	2 Credit card delinquency	3 Personal loan delinquency
Treated×Post	0.022*	0.031***	0.052*
	(0.011)	(0.013)	(0.032)
Time-varying borrower attributes	✓	✓	✓
Consumer FE	+	+	+
Year-qtr FE	+	+	+
Observations	20,686	71,957	11,544
R-squared	0.543	0.679	0.738
Dep. var. mean	0.013	0.073	0.081

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

	1 Δ Spending	2 Δ Repayment	3 Δ Balance
$Treated \times Post$	1673.4***	2345.1***	-2367.4***
	(103.7)	(121.4)	(312.3)
Time-varying borrower attributes	✓	✓	✓
Account FE	+	+	+
Year-month FE	+	+	+
Observations	342,746	342,746	342,746
R-squared	0.063	0.048	0.221
Dep. var. mean	-308.7	588.6	1610.4

Notes: This table shows the difference-in-differences estimates of the effect of wildfire on credit card spending, repayment, and balance. 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 8. Heterogeneous Effects of Camp Fire on Credit Card Balance and Delinquency

	Homeowners		Renters	
	1	2	3	4
Panel A: Balance	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720	Equifax Risk Scores ≤ 720	Equifax Risk Scores > 720
Treated × *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
Dep. var. 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 × *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
Dep. var. 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 14 months 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).

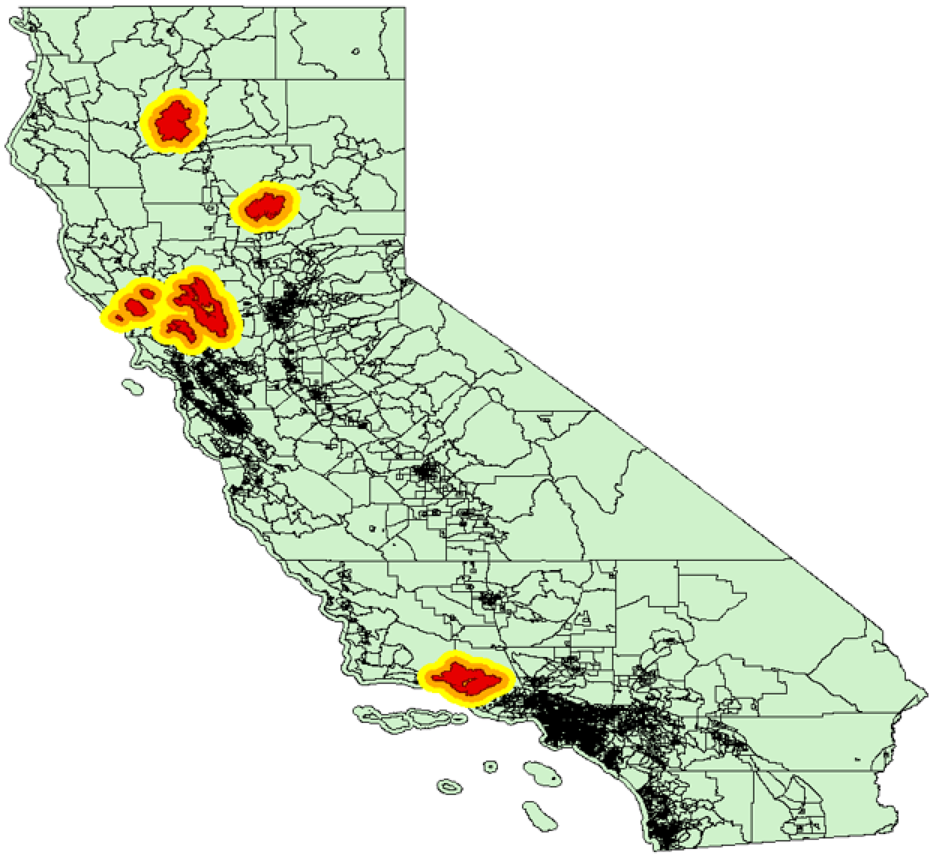


Figure A.1. Extreme Wildfires in California between 2016 and 2020 and the 1-, 5-, and 10-Mile Peripheral Rings

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.

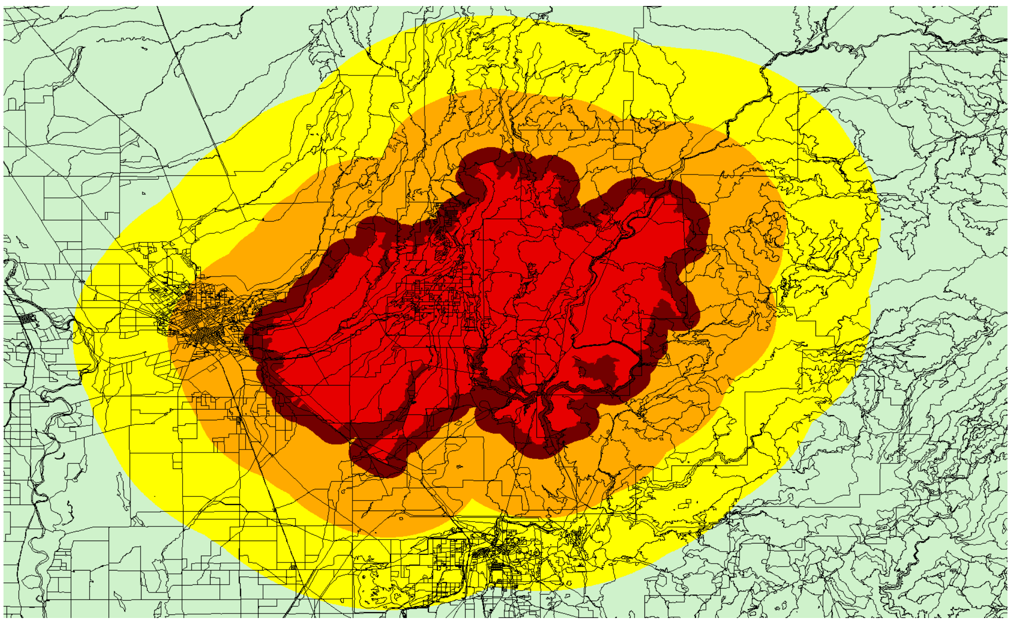


Figure A.2. Treatment and Control Areas in the Camp Fire Analyses

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.

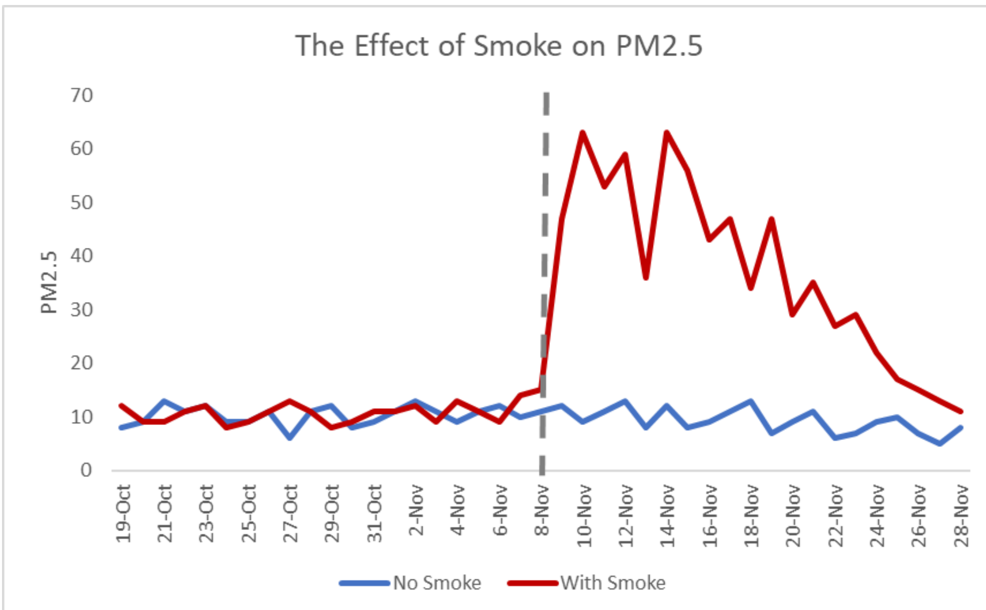


Figure A.3. Wildfire Smoke Elevated $PM_{2.5}$ After the Camp Fire

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:

$$PM_{2.5_{z,d}} = \sum_{\tau=-20}^{20} \beta_\tau * SmokeDay_{z,d+\tau} + \alpha_{z,day-of-year} + \varepsilon_{z,d}. \tag{5}$$

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 $\mu g/m^3$. Sources: NOAA's Hazard Mapping System (HMS) and EPA's Air Quality System.

Figure A.4. Effects 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 are 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, which occurred in California during November 2018. Sources: Federal Reserve Bank of New York Consumer Credit Panel/Equifax data (CCP).

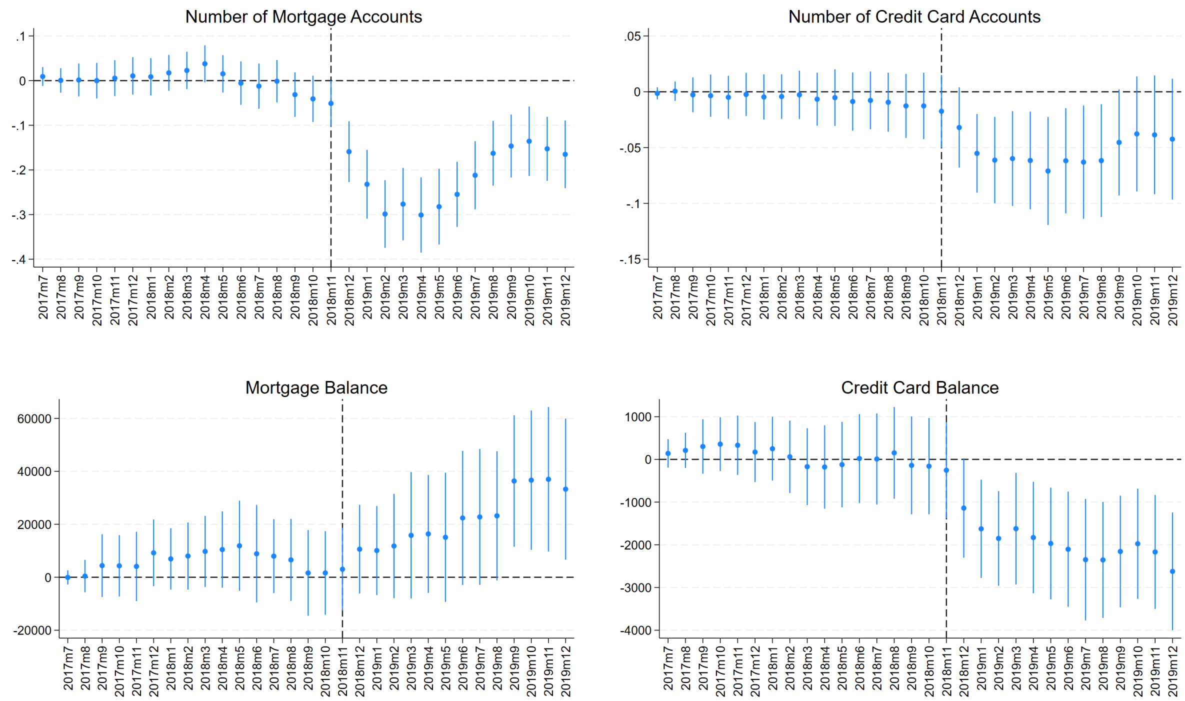


Figure A.5. Effects of 2018 Camp Fire on Credit Balance and Number of Accounts - From the CRISM Data

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 are restricted to households that experienced no change in the number of accounts. The figure shows the time dynamic patterns from the CRISM. The time frame of the analysis is 14 months before and after the Camp Fire, which occurred in California during November 2018. Sources: Equifax Credit Risk Insight Servicing and ICE, 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. (2023), 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 14 months before and after each of the four wildfires. Age is defined as 2022 minus the birth year reported in the CCP. The table shows the average among the four different fires (Camp, Carr, Thomas, and LNU Complex fire). 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							
$PM_{2.5}$	36.76	17.98	20.95	31.87	31.87	18.22	73.61
$PM_{2.5}$ 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							
$PM_{2.5}$	39.98	7.21	33.50	37.49	46.11	30.75	53.02
$PM_{2.5}$ 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							
$PM_{2.5}$	18.28	10.64	10.37	15.26	19.07	5.62	47.31
$PM_{2.5}$ 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							
$PM_{2.5}$	16.78	3.01	14.95	16.43	18.41	10.72	28.06
$PM_{2.5}$ 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) Lab, 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 - 30 to 100 Miles

	1 Mortgage Delinquency	2 Credit Card Delinquency	3 Personal Loan Delinquency
$Treated \times Post$	-0.002	0.007***	0.013**
	(0.003)	(0.003)	(0.006)
Time-varying borrower attributes	✓	✓	✓
Borrower FE	+	+	+
Q-year FE	+	+	+
Observations	656,420	1,811,511	339,604
R-squared	0.524	0.745	0.781
Dependent variable	0.018	0.067	0.084

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., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ smaller than 5 $\mu g/m^3$), before and after the Camp Fire. The time frame of the analysis is 14 months before and after the Camp Fire. We focus on zip codes located 30 to 100 miles from the Camp Fire. 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: 30 to 100 Miles From the Fire

	1	2	3
IV Estimates	Δ Spending	Δ Repayment	Δ Balance
$Treated \times Post$	393.0***	-231.2*	1138.4**
	(98.7)	118.2)	(454.7)
Time-varying borrower attributes	✓	✓	✓
Account FE	+	+	+
Year-month FE	+	+	+
County by quarter FE	+	+	+
Observations	1,664,688	1,664,688	1,664,688
Adjusted R-squared	0.086	0.049	0.448

Notes: This table shows IV estimates of the effect of wildfire-related air pollution on credit card spending, payment, and balance 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., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ smaller than 10 $\mu g/m^3$), before and after the Camp Fire. The time frame of the analysis is 14 months prior to and 14 months 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, etc. 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. Effects of Camp Fire-Induced Pollution on Credit Card Spending and Repayment: Northern and Central California

IV Estimates	1 Δ Spending	2 Δ Repayment	3 Δ Balance
$Treated \times Post$	520.7***	-275.8*	1172.2**
	(192.5)	(148.3)	(635.3)
Time-varying borrower attributes	✓	✓	✓
Account FE	+	+	+
Year-month FE	+	+	+
County by quarter FE	+	+	+
Observations	734,623	734,623	734,623
Adjusted R-squared	0.062	0.029	0.471

Notes: This table shows IV estimates of the effect of wildfire-related air pollution on credit card spending, payment, and balance, in a difference-in-differences framework. We study the whole California region north of Los Angeles that was affected by smoke from the Camp Fire. We compare borrowers that were in zip codes exposed to heavy pollution (e.g., $PM_{2.5}$ greater than 40 $\mu g/m^3$) to those in zip codes exposed to light pollution (e.g., $PM_{2.5}$ smaller than 10 $\mu g/m^3$), before and after the Camp Fire. We conduct a propensity score match between the highly polluted zip codes (treated) and the lightly polluted zip codes (control) based on zip code income, race, and homeownership ratio from the Census. The time frame of the analysis is 14 months prior to and 14 months 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, etc. 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.7. Heterogeneous Effects of Wildfire-Induced Pollution on Credit Card Spending and Repayment: Different Fires

Panel A: Δ Spending	1 Camp Fire	2 Thomas Fire	3 Carr Fire	4 Central LNU
$Treated \times Post$	548.8***	398.2	864.0***	141.4
	(163.9)	(576.4)	(396.2)	(294.5)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Month-year FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	727,110	160,516	92,115	381,834
R-squared	0.080	0.100	0.053	0.045
Dependent variable mean	-249.7	-347.3	-245.4	-296.7
Panel B: Δ Repayment	Camp Fire	Thomas Fire	Carr Fire	Central LNU
$Treated \times Post$	-629.5**	-280.5	-1636.3***	-258.5
	(263.2)	(406.3)	(118.8)	(292.5)
Time-varying borrower attributes	✓	✓	✓	✓
Account FE	+	+	+	+
Year-Month FE	+	+	+	+
County by quarter FE	+	+	+	+
Observations	727,110	160,516	92,115	381,834
R-squared	0.048	0.051	0.022	0.027
Dependent variable mean	216.2	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 75th 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 14 months 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, 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: Stanford University Environmental Change and Human Outcomes (ECHO) Lab for air pollution data; Federal Reserve Y-14M for credit card data.