Wildfires, Smoke Pollution, and Household Purchasing Behaviors

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Abstract

In this paper, we investigate households' behavioral responses to wildfires in California to better understand their mitigation and adaptation strategies. We combine daily household-level consumer purchase data from the NielsenIQ Consumer Panel with detailed daily data on wildfire incidents and smoke exposure from various sources. Our analysis shows that while overall spending decreases during wildfires, likely due to evacuations, the opposite occurs during wildfire-related smoke events, where spending increases, particularly on essential goods, indicating adaptive behavior. However, households' response to wildfires and smoke is often delayed, suggesting a lack of immediate disaster awareness. Experienced households tend to respond more cautiously, and we observe significant heterogeneity in responses based on income, age, and pre-existing health conditions. These findings shed light on the complex and varied ways households adjust to wildfire-related disruptions.

Keywords: natural disaster, wildfire, air pollution, avoidance behavior, NielsenIQ consumer panel

JEL classification codes: D12, Q54, Q58

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1 Introduction

Climate change is leading to more frequent and severe natural disasters, including wildfires fueled by increased drought and elevated temperatures (Mansoor et al., 2022). Since the 1970s, the Western United States has experienced a fourfold increase in the number of wildfires consuming more than 400 acres, while globally, fire season length has increased by more than 18% (Westerling et al., 2006; Jolly et al., 2015). Wildfires can result in injuries, loss of life, and significant property damage. Additionally, deteriorating air quality, specifically elevated particulate matter concentrations from wildfire smoke, poses serious risks to human health and worsen birth outcomes (Reid et al., 2016; Heft-Neal et al., 2022). Despite these widespread consequences, the human and economic impacts of wildfires remain understudied.

In this paper, we explore two key research questions. 1) Do households respond to wildfires and smoke pollution to mitigate negative health impacts? If so, how do these responses manifest in their purchasing behaviors? 2) Do mitigation and adaptive behaviors differ across households? Specifically, does prior wildfire experience influence adaptation, and do vulnerable households take more precautions than others?

Recent research has shown that increased damage and future risk of wildfires have lowered the economic value of western timberland by nearly 10% over the last two decades (Wang and Lewis, 2023). Despite this, many households remain exposed, and efforts to limit development near vulnerable areas have been minimal. Baylis and Boomhower (2023) use data on firefighting expenditures to estimate implicit subsidies for homes in the western US, finding that these subsidies sometimes exceed 20% of home value. They also show that the public provision of fire protection has spurred a 2.5% increase in development in high-risk areas. In contrast, Black, Irwin and McCoy (2023) find that "saliency shocks" from wildfires in Colorado lead to significant decreases in the rate of new development in areas at risk of wildfire in Colorado and that this effect persists for five years.

A smaller body of literature examines the macroeconomic impacts of wildfires. Walls and Wibbenmeyer (2023) report mixed effects of western US wildfires on employment, with fires boosting job growth in the construction sector but reducing employment growth by 1.3 percentage points in nearby areas during the year of the fire, with no significant longer-term effects. Similarly, Meier, Elliott and Strobl (2023), using panel data from Europe, find that wildfires decrease contemporaneous GDP and have mixed effects on employment, reducing jobs in tourism and retail but increasing employment in insurance, real estate, and support service sectors.

Less research has been done on the household-level impacts of wildfires. Ho et al. (2023) investigate the impacts of the 2016 Fort McMurray wildfire in Canada on consumers' finances, finding the fire increased mortgage arrears in the hardest hit areas. Wildfire smoke has also been shown to negatively impact student test scores (Wen and Burke, 2022). Recent research has also shown that residents in higher-income areas search for more information about air quality during wildfires and stay home more (Burke et al., 2022).

This paper is one of the first to assess the micro-level impacts of wildfires on households, as well as to investigate averting behavior. Combining various wildfire and wildfire smoke measures for the state of California with daily, household level data on retail store trips and purchases from the NielsenIQ Consumer Panel Data, we assess the impact of wildfires on both trips to retail stores and expenditures on various categories of goods. We find that while retail trips remain largely unchanged, overall spending decreases during wildfires, likely due to evacuations. In contrast, spending increases during wildfire smoke events, particularly for essential goods like air purifiers, face masks, and groceries, enabling households to "hunker down" and limit exposure.

Households with prior wildfire experience respond more cautiously, avoiding trips during wildfires and stocking up during smoke events, whereas those below the poverty line appear less aware of smoke risks, and those with vulnerable-aged members may be less prepared.

Moreover, we examine the cumulative effects of extended exposure to wildfires and smoke. Wildfires in proximity initially reduce shopping activity due to evacuations but later increase trips and spending as households restock. Prolonged smoke exposure leads to a small initial increase in retail trips, followed by declines as households adapt by staying indoors. Minimal early impacts suggest limited initial awareness of fire and smoke hazards.

The reminder of the paper is organized as follows: Section 2 describes the data, including wildfire, smoke, and household-level retail shopping measures. Section 3 outlines the methodology for estimating the effects of wildfires and smoke. Section 4 presents the results, and Section 5 concludes with policy implications.

2 Data

We focus our analysis on the state of California because wildfires are a major and increasing concern and due to tractability. Furthermore, sorting within California is less likely to be an issue than across a larger geographic area. We match wildfire and smoke data from various sources geographically to the zip code area where households in our consumer panel reside.

2.1 Wildfire

We obtain wildfire data from the Interagency Fire Occurrence Reporting Modules's Fire Occurrence Data Records. This dataset contains information on fire events, including the incident's name, start and end dates and times, location, acreage burnt, and event type (i.e., prescribed fire vs. wildfire). We focus only on the wildfire events that burnt at least one acre of land. Small fires may have minimal impacts on households, and households may react to prescribed fires differently from wildfires. We match these fires based on their coordinates to zip codes, using the maps of the zip code tabulation areas of 2000 and 2010 from the National Historical Geographic Information System (NHGIS) of IPUMS.[1]

Our first fire measure is a binary indicator for whether one or more fires (of at least one acre) are located within a household's zip code. Because households may respond to nearby fires not within their zip code, we also utilize indicators for having a fire within 30, 50, or 100 miles of the zip code centroid. Table 1 presents the summary statistics of treatment measures at the day-zip-code level. About 0.02% of the zip-day observations in the sample have fire points inside the zip code area, 0.1% have fire points within 30 miles, close to 0.2% within 50 miles, and more than 0.2% within 100 miles.

2.2 Smoke

We acquire the smoke data from two sources. First, we utilize the publicly available data from Childs et al. (2022) as our main measure of wildfire smoke. The authors assemble various ground, satellite, and reanalysis data and develop a machine learning model to generate daily, 10 square

[1] Given the availability of the Nielson data, we focus on the wildfire incidents from 2006 through 2019. We merge the data of the years before 2010 to the zip code map 2000 and the years 2010-19 to the zip code map 2010.

kilometer estimates of wildfire smoke-driven PM2.5 (particulate matter with a diameter of 2.5 microns or less) concentrations for the US from 2006-2020.[2] Such fine particulate matter is of particular concern to public health, contributing to respiratory and cardiopulmonary illness and even mortality (e.g., Xing et al., 2016). One advantage of this data over the second source of smoke data (discussed in the following paragraph) is that, since it is predicted, there are fewer observations with a measure of zero, resulting in more identifying variation.[3,4]

The second source is the Geostationary Operational Environmental Satellite (GOES) Products Server of the NOAA Satellite and Information Service. The shapefiles of smoke polygons are available daily from August 2005 to the end of 2021. These files include the coordinates of the polygons, the start and end times of smoke, and its density.[5] We merge these shapefiles with the maps of the zip areas from NHGIS. We consider two treatments: whether a smoke polygon interacts with the zip code area and the number of hours that smoke lasts in a day.

The summary statistics of the smoke measures are also displayed in Table 1. The sample mean of wildfire PM2.5 concentration is 0.4 μg/m^3, and its maximum is 427 μg/m^3. About 0.9% of zip-day observations are impacted by wildfire smoke; the smoke lasts 0.03 hours per day on average, with the maximum being 19 hours.

2.3 NielsenIQ Consumer Panel Data

We obtain NielsenIQ Consumer Panel (CP) Data via Kilts Center for Marketing Data at the University of Chicago Booth School of Business. The CP data includes household and trip-level retail store purchases by a nationally representative sample of 40,000-60,000 panelists annually.Participants are asked to record all their purchases intended for personal, in-home use, whether they occur in-store, online, or via delivery services. The data collection process aims to capture consumer behavior across all shopping channels

[2]Throughout this manuscript we refer to this data alternately as wildfire or wildfire-driven PM2.5, predicted PM2.5, wildfire smoke, or simply PM2.5.

[3]According to the National Ambient Air Quality Standards for Particle Pollution, the 12-hour average of the maximum amount of pollutants that can be present in outdoor air without harming human health is 35μg/m^3; a level of 35-55 μg/m^3 is considered unhealthy for sensitive groups, a level exceeding 55 μg/m^3 is unhealthy for the general population. (Source: US Environmental Protection Agency)

[4]To distinguish PM2.5 from wildfires from other sources, we also acquire data on daily mean PM2.5 concentration by county measured by the US Environmental Protection Agency (EPA).

[5]Smoke density is categorized as light, medium, and heavy.

We utilize only observations from California from 2006-2019, which include approximately 3,500-5,000 panelists per year. The CP data include the price and quantity of goods purchased, the date of purchase, and the location of purchase (at the three-digit zip code level), as well as respondent and household socio-demographics and county and zip code of residence. Most panelists use a phone app to scan receipts. However, those without phones or internet are either given a scanner or instructed to keep receipts in a "dustbin" for collection by a NielsenIQ representative at regular intervals.

The Federal Emergency Management Agency recommends using N95 masks and preparing to evacuate when a wildfire is nearby.[6] The California Department of Forestry and Fire Protection recommends having a "Go Bag" ready in case a household evacuates due to the threat of a wildfire. They suggest including in this bag a three-day supply of non-perishable food and three gallons of water per person, as well as a first aid kit, sanitation supplies, a flashlight, and a battery-powered radio with extra batteries.[7] In addition to a similar "Go-Kit," the American Red Cross also recommends preparing a "Stay-at-Home Kit" with two weeks of supplies.[8]

Given the above recommendations, we investigate the impacts of wildfires and smoke on purchases of four categories of goods: avoidance goods, emergency goods, groceries, and perishable foods. Avoidance goods include air purifiers, their filters, and external breathing aids (i.e., face masks). Emergency goods include bottled water, batteries and battery chargers, flashlights, and flashlight bulbs. Groceries include dry grocery, frozen foods, dairy, packaged meat, and fresh produce but exclude bottled water. Perishable foods include bread and baked goods, butter and margarine, cheese, cottage cheese, sour cream, toppings, eggs, fresh meat, fresh produce, milk, and yogurt. We also use the number of trips taken and the total expenditures in the CP data as outcomes of interest. Table 2 summarizes these data.

Notably, while NielsenIQ takes measures to ensure households actively scan their purchases and will remove from their sample households who repeatedly or persistently do not report purchases, we cannot perfectly rule out the possibility that some households may forget to scan their purchases or throw away their receipts in the days and weeks around a wildfire. It is

[6] See https://www.ready.gov/sites/default/files/2024-08/ready-gov_wildfire_info-sheet.pdf.

[7] See https://readyforwildfire.org/prepare-for-wildfire/emergency-supply-kit/.

[8] See https://www.redcross.org/get-help/how-to-prepare-for-emergencies/types-of-emergencies/wildfire.html# text=You%20may%20have%20to%20leave,financial%2C%20and%20medical%20records%20safe.

worth noting that the receipts do not need to be scanned immediately; they can instead be scanned even weeks after the purchase date. Nevertheless, if households scan purchases less than required during a wildfire, we would underestimate households' response. Specifically, any positive significant coefficients (increases in trips or expenditures) would be underestimated, while any negative significant coefficients could partially result from failure to scan receipts. That said, we find no significant impact of wildfires on number of trips taken, but significant impacts on expenditures. If results were driven by under-reporting, we would expect to see a decrease in trips, which we do not.

2.4 Ailment Data

We acquire information on household ailments from the NielsenIQ Annual Ailments, Health, and Wellness Survey. This survey complements NielsenIQ Consumer Panel Data and contains information about panelists' ailments and illnesses. However, it is conducted annually beginning only in 2011 on a sub-sample of the CP.

We identify a list of ailments or pre-existing conditions that could be caused or exacerbated by exposure to smoke pollution, including respiratory diseases, cardiovascular diseases, allergies, eye diseases, neurological conditions, skin issues, anxiety and depression, and illnesses resulting in compromised immune systems. Among these ailments, smoke pollution has the most direct impact on respiratory problems, such as asthma, bronchitis, and pneumonia. Appendix Table A1 displays the list of ailments that we use to define the ailment status of a household. Individuals with such ailments are particularly vulnerable to the adverse effects of smoke inhalation, and they may respond to wildfire and smoke differently from healthy individuals.

Table 3 reports the summary statistics of household demographics for the whole sample, the treated groups, and the sub-sample with ailment information available. Noticeably, the wildfire-treated sample is slightly less educated and more white with lower income than the others. While wildfire smoke can be widespread and impact the whole of California, the risk of wildfires themselves may vary across locations within the state. To address the concern that households may sort into the residential locations according to the wildfire risk, we estimate the propensity score of a zip area to experience a wildfire within 50 miles in a year. As a robustness check, we trim the sample according to the propensity score so that the treated and untreated locations are more comparable and run regressions on the trimmed samples.[9]

3 Empirical Methodology

3.1 Contemporaneous Effect

We first investigate the contemporaneous effects of wildfire and smoke pollution on household purchasing behaviors. The National Weather Service issues Fire Weather Watches and Red Flag Warnings when expecting high winds and dry conditions conducive to wildfires.[10] However, forecasting wildfire is difficult: even the best available science allows for little more than a day of prediction (Radocaj, Jurisic and Gasparovic, 2022; Kormann, 2023). Indeed, anecdotal evidence suggests little to no awareness (in terms of Google search interest) of major wildfires even one to two days before they begin, as shown in Appendix Figure A1.

Therefore, we focus on the contemporaneous impacts of wildfires and smoke pollution instead of households' pre-disaster preparation.[11] We estimate the following equation:

$$Y_{ht} \quad = \quad \beta Treatment_{zt} + \gamma_1 \sum_{\tau=1}^{7} Y_{ht-\tau} + \gamma_2 X_{ht} + \gamma_3 AQ_{ct} + yr_t + mo_t + dow_t + f_c + \varepsilon_{ht}. \quad (1)$$

Here, Y_{ht} stands for the outcome of interest, namely, the number of retail trips, the total expenditures, or the expenditure on a particular category of goods that household h makes on day t. We consider the following treatment variables: a binary indicator for whether there is one or more wildfire points in the zip area of residence z on day t, indicators for whether one or more fire points are within 30 miles, 50 miles, or 100 miles from the centroid of the zip code area, a binary indicator for wildfire smoke, and two continuous measures of smoke intensity -the number

[9] We estimate the propensity score at the zip-year level using the latitude and longitude of a zip code area centroid, as well as their quadratic terms, of each zip area, the distance to the ocean and its square, elevation and its square, share of water body, climate zone, and year fixed effects. Appendix Figure A1 displays the propensity score distributions for the treated vs. untreated locations. We trim the sample to include the zip-year observations with a propensity score between 0.1 and 0.9. We present the baseline results estimated using the propensity-score-trimmed sample and present them in Appendix Table A2. The results are reassuring.

[10] The specific requirements for watches and warnings vary by location- see, for example, https://www.weather.gov/dtx/fire_defs and https://www.weather.gov/bou/RFW_Definitions. The consistency and effectiveness of these warnings and watches have been called into question by relevant agencies: https://www.drought.gov/sites/default/files/2020-10/RedFlagFlyer508C.pdf.

[11] We also test specifications that include treatment leads but do not find evidence of pre-treatment behavioral changes. The results are available upon request.

of hours that smoke lasts on day t and the predicted PM2.5 concentration. All seven measures vary at the zip code area by day level.

Notably, wildfires may impact households through multiple channels. On one hand, a fire may burn near a household, threatening lives and property. On the other hand, smoke from the fire may impact areas near the fire and locations far away, depending on prevailing winds, leading to deteriorated air quality and increased PM2.5. To distinguish these channels, we consider an additional specification that includes both a fire indicator and a smoke measure, as well as their interaction.

Moreover, many households go grocery shopping on a weekly basis, and their current purchase quantity and expenditure depend on their previous recent purchases. Accordingly, we control in the regression for the number of trips or the expenditures made in the previous week, $\sum_{\tau=1}^{7} Y_{ht-\tau}$. We control for household characteristics in X_{ht}, including household income, size, if the householders are married, the age of the household head, his or her educational attainment, and race/ethnicity, as these characteristics may be correlated with the demand for groceries and other types of goods. Because household shopping behaviors may vary over time and across months of a year and days of a week, we control for year, yr_t, month, mo_t, and day-of-week, dow_t, fixed effects. County fixed effects, f_c, are also included as a control, since local public goods and policies are often administrated at the county level, and households are likely sorted along county boundaries.[12] To ensure our estimates isolate the impact of wildfires (rather than prevailing air quality), we also control for daily mean PM2.5 concentration at the county level, AQ_{ct}, as measured by and obtained from the US Environmental Protection Agency.[13] Because the impact of a wildfire can be widespread, we cluster the standard errors at the county level.

[12] We also experiment with replacing the county fix effects with household and zip code fixed effects. The estimation results are similar and available upon request.

[13] The correlation between wildfire predicted PM2.5 and EPA-measured PM2.5 is 0.39. When there is wildfire PM2.5, EPA-measured PM2.5 is elevated. Average EPA PM2.5 in our data is $11.1\mu g/m^3$. When wildfire PM2.5 exceeds 0, 20, 35, 50, or $100\mu g/m^3$, EPA PM2.5 averages 14.6, 55.6, 76.3, 91.6, and $146.5\mu g/m^3$, respectively. However, the reverse is not true. When EPA PM2.5 exceeds 35 or $50\mu g/m^3$, wildfire PM2.5 averages only $1.8\mu g/m^3$, which suggests that PM2.5 can be from many sources other than wildfires. We also experimented with replacing the wildfire-induced PM2.5 using the EPA-measured PM2.5 and reran all the regressions. Our findings indicate that household purchases of avoidance goods increase with EPA-measured PM2.5, albeit to a lesser extent than with wildfire PM2.5. However, we found no significant impact of EPA-measured PM2.5 on the number of retail trips, overall expenditures, or other categories of purchases.

Given the large number of treatment effects we try to estimate for various outcomes, we implement the Anderson (2008) method for multiple-inference corrections to reduce the likelihood of false positives.

3.2 Cumulative Effect

Wildfires and smoke can last for a prolonged period. While households may only react to the fire or smoke pollution of the day, their responses may differ based on how long they have already been exposed.

Therefore, we estimate the cumulative effects of wildfire and smoke pollution using the following equation:

$$\begin{aligned} Y_{ht} &= \sum_{i=1}^{T} \alpha_i Treatment_{zt}^{i} + \gamma_1 \sum_{\tau=1}^{7} Y_{ht-\tau} + \gamma_2 X_{ht} + \gamma_3 AQ_{ct} \\ &\quad + yr_t + mo_t + dow_t + f_c + \varepsilon_{ht}. \end{aligned} \tag{2}$$

T denotes the maximum span of consecutive treatments. $Treatment_{zt}^{i}$ is a binary indicator for household h experiencing the i^{th} day of treatment on day t, and α_i captures its effect. The other controls are the same as Equation 1.

4 Results

4.1 Contemporaneous Effects of Wildfires

4.1.1 Total Retail Trips and Expenditures

We start by investigating the contemporaneous effects of wildfires and smoke on overall shopping behavior. Table 4 presents the estimates of the seven treatment measures on the count of daily household retail store trips (Panel A) and total daily expenditure at retail stores (Panel B).[14] A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson correction (i.e., loses one significance star). A double underline

[14] Tables A3 and A4 repeat the analyses from Tables 4 and 6 using more severe wildfires that burned more than 10 acres, rather than our main estimates that utilize fires that burned more than one acre. The treatment coefficients remain insignificant, partially due to limited power, as there are considerably fewer such fires in the data.

under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

We find no statistically significant impact of wildfires or smoke on the number of retail trips but some significant impacts on total retail expenditure. Thus, in aggregate, households respond along the intensive margin (how much they purchase) rather than the extensive margin (whether they go shopping in the first place).

In particular, a nearby wildfire may cause households to spend slightly less. The estimate in Panel B, Column 2 shows that living within 30 miles of a wildfire leads households to reduce their retail expenditures by \$0.14, just over 2% of the daily average.

One possible explanation for the decrease in expenditure is that households evacuate or plan to evacuate and, therefore, do not buy as many items. They may still go to the store to buy necessities but spend less than they otherwise would have. Unfortunately, we cannot determine which households evacuated in our data. [15,16]

Another possible explanation for the decrease in expenditure (but not trips) when a wildfire is nearby is power outages. In several western states, including California, utilities plan power outages when weather conditions indicate high wildfire risk.[17] Wildfire events themselves could also damage infrastructure and lead to power outages. Households expecting or experiencing a power outage may reduce purchases of certain items like perishable food. Nevertheless, we should caution that the negative coefficient in Column 2 Panel B becomes insignificant after the Anderson correction.

In addition, we find that households increase their retail expenditures in response to wildfire smoke. Column 7 of Panel B shows that for each $100\mu g/m^3$ increase in wildfire PM2.5, households

[15] While we observe the retail stores households visit each trip, these stores are identified at the three-digit zip code level. Three-digit zip areas can be very large, capturing both a household's home location and locations further away to which they may have evacuated. Furthermore, households living near the boundary of their three-digit zip code might routinely shop at stores in other three-digit zip codes.

[16] In an attempt to identify possible evacuations, for each household-year in the data, we identified the five retail stores which the household most frequents. Then, we created an indicator for whether they visit one of these "top five stores" each day. We estimate our baseline model using this binary indicator as the outcome variable to assess if households are more or less likely to shop at these top five stores during a wildfire. A negative coefficient would suggest that during a wildfire, households are less likely to shop at their most frequented retail outlets, which, combined with evidence that they do not take fewer trips in total, may suggest they have evacuated and are shopping outside their usual radius. Although the coefficients for having a fire within one's zip code and within thirty miles of one's zip code are negative, none of these coefficients are statistically significant.

[17] See https://www.cpuc.ca.gov/psps/.

increase their expenditures by \$0.3. As such, if PM2.5 increases from zero to $35\mu g/m^3$, a level harmful to sensitive groups, daily spending would increase by over \$0.10, nearly 2% of average daily expenditures. Because the impact of PM2.5 may be nonlinear, we also create binary indicators based on the range of PM2.5 to replace the continuous treatment variable. We rerun the regressions in Column 7 with the binary indicators but find limited evidence that households only respond to a certain level of PM2.5.[18]

Notably, while nearby wildfires correlate with smoke pollution, the impacts of fires and smoke can differ. To distinguish between the direct threat from a wildfire and the impacts of smoke pollution, we estimate Equation 1, including a binary indicator for wildfires, a measure of smoke, and the interaction between the two. Table 5 presents the results. Again, we find no significant impacts on the number of retail trips, and wildfire-driven PM2.5 leads to small though significant increases in total expenditures. Only one interaction term is moderately significant- in Column 4, the estimates suggest that all else equal, smoke leads to less spending if a wildfire is burning within 50 miles of a household. Specifically, a $100\mu g/m^3$ increase in PM2.5 leads to a \$2.7 decrease in retail expenditures. This could be because when a fire is present, a higher PM2.5 level likely indicates the fire is closer. When a fire is closer, there may be a higher likelihood of evacuation or power outage.

4.1.2 Categories of Purchases

We next explore purchases by category of goods to assess what households are spending more or less money on. Table 6 displays the impacts of various wildfire measures on daily household expenditures on four different categories of goods: avoidance goods (including air purifiers and face masks), emergency goods (including bottled water and flashlights), groceries, and perishable foods. Each coefficient represents the coefficient of interest from a separate regression, which also includes day of week, month, year, and county fixed effects, as well as household characteristics, daily mean (EPA-measured) PM2.5 concentration, and prior seven-day total expenditure on the category of good. The dependent variable is the daily expenditure on each category of goods.

[18]We generate dummy variables for PM2.5 being below 12, between 12 and 35, 35 and 55, 55 and 150, or above 150 $\mu g/m^3$, respectively. These cutoffs are used according to the EPA air quality standards. Appendix Table A5 reports the estimates. While the coefficients are larger on the indicators for higher levels of PM2.5, the differences across levels are not statistically significant.

As shown in Table 6, we find a significant but small decrease in the purchase of avoidance goods when a household lives in a zip code with a wildfire. While somewhat counter-intuitive, this could be explained by evacuation. If households evacuate to safe areas, they may not need avoidance goods. When there is a wildfire within 30 to 100 miles away, households decrease their expenditure on emergency goods by just under \$0.01, or 10% of the daily average. However, after the Anderson correction, these coefficients become less significant. It is worth re-iterating the discussion in Section 2.3. If households fail to report their purchases, which is probably most likely during an emergent situation or perhaps an evacuation, any positive significant coefficients would be underestimated, while any negative significant coefficients could be a direct result of failure to scan receipts. Nevertheless, if households fail to scan their receipts, then we would also expect to see a decrease in the number of trips taken during wildfires, which we do not (Table 4). Power outages are less likely to explain our results, as they likely cause households to purchase fewer perishables (which we do not find) but not necessarily fewer emergency goods (which we do find).

Wildfire-driven PM2.5 leads to larger and significant increases in expenditure on avoidance goods and groceries, including perishables. A $100\mu\text{g/m}^3$ increase in PM2.5 leads to a \$0.013, \$0.23, and \$0.09 increase in expenditures on these categories, respectively. Thus, a $35\mu\text{g/m}^3$ increase in wildfire PM2.5 leads to a nearly 114% increase in spending on avoidance goods and a 2.6% and 3.9% increase in spending on groceries and perishables, respectively. These estimates suggest that households are generally aware of the air pollution caused by wildfires and purchase goods to protect them from exposure. To a smaller extent, households also buy extra groceries, which may allow them to stay indoors in the following days.

One concern is that prices (and therefore expenditures) could change due to the wildfire without corresponding changes in quantities of purchases. Notably, some literature on hurricanes suggests minimal impacts of disasters on retail prices (Gagnon and López-Salido, 2019; Beatty, Lade and Shimshack, 2021). Furthermore, given that it is more challenging to forecast wildfires (Radocaj, Jurisic and Gasparovic, 2022) and that smoke can shift with the wind, it is unlikely that stores have the time to adjust prices in real time during a wildfire event. Nevertheless, we perform a robustness check to address this concern using the purchase quantity of each type of good instead of the expenditure. Notably, for most categories of goods in our analysis, the quantities are not all in the same units in the CP data. For example, even within the bottled water category, some products are quantified in counts and some in ounces. However, for air purifiers and external breathing aids, all purchases are quantified in counts. Therefore, we perform a robustness check using the count of purchases rather than expenditures on the avoidance good category. Appendix Table A6 displays the results, which are consistent with those in Table 6.

In summary, wildfires induce households residing nearby to spend less overall at retail stores, though not necessarily to make fewer trips, which may be a result of evacuations. Households do, on the other hand, significantly increase their expenditures in response to wildfire-induced PM2.5. They spend more on groceries, including perishables, and especially avoidance goods like air purifiers and face masks that may mitigate health impacts of smoke inhalation.

4.2 Heterogeneous Effects

4.2.1 Past Experience

In this section, we investigate the impact of experience on households' behaviors to understand their adaptation to wildfires. Tables 7 and 8 include the wildfire treatment indicators (one regression per column), with each indicator interacting with an experience indicator. Table 7 shows effects on retail trips and total expenditure, while Table 8 examines expenditure on various categories of goods. We use two alternative experience definitions: 1) an indicator equal to one if the household lives in a zip code that was located within 50 miles of a fire point during the prior calendar year (Panel A), and 2) an indicator equal to one if the household lives in a zip code that experienced at least one day with wildfire PM2.5 concentration greater than $35\mu g/m^3$ in the prior calendar year (Panel B).[19]

According to Column 1 in Panel A of Table 7, "inexperienced" households (who did not experience a wildfire within 50 miles of their zip code the prior year) increase the number of daily trips taken by 0.06 when there is a wildfire within their zip code, a 13% increase in trips relative to the sample mean of 0.47. However, this estimate becomes statistically insignificant after the Anderson correction. Experienced households, on the other hand, *decrease* the number of trips taken by around 0.09. Experienced households may behave more cautiously and be less

[19]The 10th percentile of the number of days with wildfires in the previous year is five, the median is 27, and the maximum is 183. About 10% of the households in the sample experienced one or more days with a PM2.5 concentration greater than $35\mu g/m^3$ in the previous year.

likely to venture out during a wildfire than inexperienced households; the former may also be more likely to evacuate.

We find almost no difference in expenditures in total or on a specific good category by fire experience, except Column 6 Panel A of Table 8, which shows that households who experienced a fire the prior year purchase more emergency goods when there is wildfire smoke. Compared to inexperienced households, experienced ones may have a higher awareness of potential wildfire-related power outages.

Panel B of Tables 7 and 8 shows the effect of wildfire smoke experience. The results in Panel B Table 7 suggest that households with smoke experience are more responsive to PM2.5 levels, making more retail trips and purchasing more goods. A 100μg/m^3 increase in PM2.5 results in 0.03 more trips and a \$0.3 increase in total expenditures among experienced households, while PM2.5 shows no significant impacts on inexperienced households.

The treatment-experience interactions in Columns 7 and 10 in Panel B Table 8 suggest that households with smoke experience purchase fewer groceries and perishables (30% and 42% less than inexperienced households, respectively) when there is a fire in their zip code. They may be more likely to evacuate or respond to planned power outages, especially by purchasing fewer perishables. Meanwhile, although there is not a significant difference between experienced and inexperienced households in their spending on avoidance goods (Column 3), experienced households stock up considerably more on groceries and perishables than inexperienced households in the presence of wildfire smoke (Columns 9 and 12). Column 2 in Panel B of Table 8 shows households with smoke experience spending less on avoidance goods when there is a fire within 50 miles. This could be because they are more likely to evacuate and not need such goods or because they already have air purifiers and face masks in stock from prior exposure.

Once again, experienced households appear to behave more cautiously. Those with prior wildfire experience are less likely to venture out during a wildfire, making fewer trips to retail stores. They may also be more likely to evacuate or better aware of potential power outages. Households with wildfire smoke experience, on the other hand, take more trips and spend more overall than treated households without experience. This increase in expenditure appears driven mainly by increased spending on groceries. This may be to stock up to stay indoors in the coming days and avoid smoke exposure.

4.2.2 Vulnerable Households

To investigate differential responses by vulnerable households, we estimate heterogeneous effects for three sub-populations: households in poverty, households with very young or old members, and households with ailments (reported in the previous year). Poor households may have tighter budget constraints and lower capacity for preparing for or responding to a wildfire. Young children and older adults, as well as those with pre-existing conditions, such as respiratory and cardiovascular diseases, are more vulnerable to harmful smoke pollution. Therefore, they must take more precautions than healthy individuals when a wildfire or smoke is present. Furthermore, evacuation may be more difficult for these households.

We determine whether or not a household is at or below the federal poverty line based on household income and size.[20] Tables 9 and 10 display the results of including an interaction between a poverty indicator and our measures of wildfire treatment into our baseline specifications. Column 2 of Table 9 shows that households below the poverty line take nearly 0.02 trips more (relative to a daily average of 0.47) than other treated households when there is a wildfire within 50 miles (not significant with Anderson correction), while Columns 4 and 5 show that these households also spend \$0.38-\$1.59 more per day when there is a wildfire (within 50 miles or within their zip code, respectively). Table 10 shows this increase in expenditure by households below the poverty line is driven by more spending on avoidance goods and groceries, including perishables, but not on emergency goods. This could be because these households are less likely to evacuate. Evacuation could be cost prohibitive for low income households, particularly those without family or close friends with whom they could stay, requiring a hotel room. Additionally, adults in these households are less likely to be salaried workers with the ability to work remotely.

There is no significant difference in overall expenditure or trips in the presence of wildfire-driven PM2.5 (Columns 3 and 6 of Table 9). However, Columns 3, 9, and 12 of Table 10 show that households below the poverty line spend substantially less than their higher-income counterparts on avoidance goods, groceries, and perishables when there is wildfire smoke. Indeed, they do not purchase more of these goods than control households. Thus, lower-income households do not appear to take the same precautionary measures as higher-income households on days with

[20] See https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references).

wildfire smoke. Given that households below the poverty line are responsive to wildfires and spend more on important goods, we suspect that the smoke results are not driven by budget constraints but rather by awareness. A nearby wildfire can be very salient, but wildfire-driven PM2.5 might be less so, particularly if it is blown from afar. Lower-income households may not have or seek as much information on wildfire smoke and air pollution. This finding is consistent with Burke et al. (2022), who find that households in higher income areas search for more information about air quality and are more likely to stay home during wildfires.

In Tables 11 and 12 we add interactions between treatment and an indicator for a household including a member who is five years old or younger and/or 65 years old or older to the regressions. The only significant differential effects in Table 11 are in Columns 4 and 5, which show that households with vulnerable-aged members spend less in total at retail stores when there is a fire within their zip code or within 50 miles, though only one of the estimates remains marginally significant after the Anderson correction. Table 12 finds these households spend less than other treated households on all four categories of goods. They also spend less on groceries on days with wildfire smoke (Column 9). The larger decrease in expenditures on avoidance and emergency goods as well as groceries and perishables by households with a vulnerable aged member during a wildfire could suggest either less preparedness or a higher likelihood of evacuation. However, these households also buy fewer groceries during wildfire smoke. While this could also be due to a higher propensity for evacuation, evacuation in response to poor air quality is less common, and this could instead suggest a lack of preparedness to stay indoors and avoid exposure.

Finally, we consider ailments, including pre-existing conditions that may make a person more physically vulnerable to wildfire smoke. The list of ailments we consider is shown in Table A1. We add to the baseline specifications an interaction between an indicator for whether a household reports one of these ailments in the previous year and the treatment variables. Tables 13 and 14 present the results. Table 13 shows no differential impacts of wildfires or smoke on trips or total expenditure by ailments. However, Table 14 shows that households in which a member has one of the ailments spend more on emergency goods when there is a fire within their zip code (Column 4), and they spend more on groceries when there is wildfire smoke (Column 9). Thus, households with ailments seem relatively better prepared to hunker down at home and avoid smoke exposure.

4.3 Cumulative Effects on Retail Trips and Expenditure

In this section, we investigate the cumulative effect of wildfire and smoke overtime on the daily count of retail trips and total retail expenditures. We estimate Equation 3 using the main three treatments: fire within a zip code, fire within 50 miles of a zip code, and wildfire smoke. Since this specification requires a binary treatment, we measure wildfire smoke using an indicator equal to one if wildfire-driven PM2.5 concentration is greater than $35\mu g/m^3$.

During our period of analysis, the longest continuous span of having a wildfire inside the zip code area and within 50 miles is three and four days, respectively; that of experiencing wildfire PM2.5 above $35\mu g/m^3$ is 23 days. We use the sequential days within a consecutive treatment period to define the treatment variables. Since most wildfires within 50 miles do not persist beyond three days, we combine the third and fourth days into a single binary indicator. Similarly, we group the days beyond the 14th day of wildfire-induced poor air quality (i.e., PM2.5$>35\mu g/m^3$) into one indicator.

Figures 1-2 display the results. For wildfires within the zip area, we observe a significant decrease in retail trips and total expenditure on the second day of the fire, followed by a sharp increase on the third day. Specifically, households make 0.1 fewer trips to retail stores and spend \$2.8 less on the second day of the fire but make one additional trip and spend \$20 more on the third day. This pattern may provide suggestive evidence of evacuation: some households may evacuate on the second day of a nearby wildfire, reducing their shopping activity; once they settle down the following day, they may go to the stores to purchase necessities.

When there is a wildfire within 50 miles, households visit retail stores more often and spend more there starting the second day of the fire. The increases may imply preparation and mitigation. However, only the coefficient on the second-day indicator is marginally significant for the number of trips.

Figure 2 shows that the number of retail trips increases slightly up to the 13th day of wildfire smoke: the increase is significant on the 6th day and marginally significant on the 5th and 11th day. While the coefficients for the first 13 days are mostly positive for total retail expenditures, they are all small and statistically insignificant. However, both the number of trips and total expenditures decrease significantly starting on the 14th day and continuing after that. In particular, households make 0.23 fewer trips on the 14th day of wildfire smoke and nearly 0.2 fewer trips afterward, reducing their expenditures by almost \$4 and more than\$5, respectively. This pattern may reflect a shift in behavior: when smoke pollution first becomes prevalent, some households may increase their retail shopping to stock up on necessities or items to protect themselves against the smoke. However, as the poor air quality persists, households may choose to stay indoors, particularly if they have already purchased what they need in the preceding days.

In addition, as shown in Figure 1, the coefficient on the first-day indicator is close to zero for both wildfire measures and regardless of the outcome. This pattern suggests that households may not even be aware of wildfires when they initially occur, let alone be adequately prepared for such disasters. Similarly, the estimated impact of wildfire smoke is rather small during the first few days in Figure 2. Importantly, PM2.5 particles are not visible to the human eye; while visibility correlates with PM2.5 levels, it is also influenced by meteorological conditions (Wang, Zhang and Yu, 2019). Consequently, individuals may remain unaware of deteriorating air quality even after multiple days of exposure.

5 Conclusion

As climate change intensifies drought and heat, leading to more frequent, severe wildfires and longer fire seasons, understanding the human costs of wildfires becomes increasingly critical. By combining household-level daily retail shopping trip data with wildfire and smoke data, we investigate the impacts of wildfires on trips and purchases.

We find that at the onset of a wildfire, households reduce their total expenditure, but do not significantly reduce the number of trips taken, likely because evacuating households prioritize fewer, essential purchases. We find very little evidence of households increasing purchases of emergency goods, which include bottled water and flash lights, finding in some cases decreases in these expenditures.

Responses to wildfire smoke are distinct. Households increase retail expenditure in response to increased wildfire-driven air pollution. A $35\mu g/m^3$ increase in wildfire PM2.5 increases spending on groceries and perishables by 3-4%, which may allow households to stay indoors to avoid exposure in the coming days, and more than double the spending on avoidance goods, which include air purifiers/filters and face masks. Households with prior smoke experience take more trips and spend more on groceries and perishables, better preparing them to hunker down. There is no experience differential in spending on avoidance goods, indicating general awareness of their importance but a learned emphasis on grocery preparedness among experienced households.

We also explore how responses vary by physical and socio-economic vulnerability. Households with members who have pre-existing health conditions are relatively better prepared, spending more on emergency goods and groceries. However, households with young children or seniors appear less prepared, purchasing fewer goods across all categories during wildfires and fewer groceries during smoke events. Similarly, households below the poverty line appear less likely to evacuate during wildfires, taking more trips and spending more on most goods except emergency items. During smoke events, these households spend less on avoidance goods, groceries, and perishables, possibly due to an information barrier, as smoke may be less salient than wildfires themselves, and is consistent with recent literature (Burke et al., 2022).

Lastly, we examine how responses evolve with prolonged exposure to wildfire and smoke. We find minimal early reaction in retail trips and spending, which may suggest a lack of immediate awareness of wildfire and smoke. Wildfires in close proximity suppress shopping activity on the second day, likely as households evacuate, but subsequently drive increased trips and spending as they may need to restock essentials. In contrast, prolonged smoke exposure leads to some uptick in retail trips during the first two weeks, which later decline as households may adapt by remaining indoors.

Many households appear to act rationally in terms of avoiding exposure to wildfires and smoke. Policy makers can continue to encourage this behavior. Given that it is difficult to predict wildfires more than a day or two ahead of time, the window of opportunity for preparation is limited. Policy makers could be more proactive prior to the start of wildfire season by encouraging households to preemptively stock up on air purifiers/filters, face masks, emergency goods, and non-perishable groceries. Investment in real-time, localized air quality monitoring systems and public dissemination tools (e.g., apps or text alerts) could help households respond more effectively to deteriorating conditions, and raise awareness of both poor air quality days and the importance of such avoidance goods in mitigating health impacts. They may also consider providing free or subsidized air purifiers to more vulnerable households. Community leaders could also provide "clean air shelters" for local residents. For example, public library and community centers could be outfitted with HEPA air purifiers and filters. Special programming for children and seniors could be provided and advertised.

The recent rise in online shopping and grocery shopping will likely benefit households as they can procure more goods without venturing out. However, the unpredictability of wildfires and potential disruptions to delivery systems may limit the effectiveness of online ordering during wildfire events. Policymakers could expand access to local grocery delivery services and offer vouchers for free delivery to vulnerable households, ensuring timely access to essential supplies during crises.

Policy makers could also incorporate our results in a benefit cost analysis evaluating wildfire mitigation programs. A back-of-the-envelope calculation based on the PM2.5 coefficient in Column 1 of Table 6, assuming only households exposed to wildfire PM2.5 in excess of $35\mu g/m^3$ spend extra, and scaling the sample by the total number of households in California, suggests that annual extra expenditures in California on avoidance goods (air purifiers/filters and face masks) due to wildfires is approximately \$345k.[21]

However, there are broader societal costs that remain less understood, such as the impact of staying home for extended periods. Households may avoid not only retail trips but also essential activities like healthcare visits, exercise, and social engagement. This behavior could increase risks of physical and mental health issues, especially for vulnerable populations. Addressing these concerns may require targeted interventions, such as community wellness programs or telehealth initiatives during prolonged smoke events.

Beyond immediate preparedness, long-term strategies like zoning restrictions in high-risk areas, incentives for fire-resistant infrastructure, and investment in public awareness campaigns are crucial for reducing future risks. Policymakers should also prioritize equitable access to resources and information, bridging gaps for low-income households and other vulnerable groups who may lack the means or awareness to prepare effectively. These efforts can build more resilient communities as wildfires become an increasingly frequent and severe consequence of climate change.

[21] Assuming households spend extra in response to any wildfire smoke results in a total of \$1.2 million.

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6 Figures & Tables

Table 1: Summary Statistics for Wildfires and Smoke

Variable	Mean	Std.Dev.	Min	Max
Fire (=1)	0.000176	0.0133	0	1
Fire within 30 Miles (=1)	0.00109	0.0330	0	1
Fire within 50 Miles (=1)	0.00165	0.0406	0	1
Fire within 100 Miles (=1)	0.00205	0.0453	0	1
Predicted PM2.5 Concentration (μg/m^3)	0.406	3.473	0	427.3
Smoke(=1)	0.00887	0.0938	0	1
Total Hours Lasted	0.0273	0.373	0	19
No. of Observations				5,698,771
No. of Zip Code Areas				849
No. of Days				5,113

Table 2: Summary Statistics for Trips and Purchases

	Mean	Std Dev.
Panel A: Unconditional Purchases Statistics		
No. of Trips	0.47	0.85
Total Expenditure	5.83	17.29
Expenditure on Category		
Avoidance	0.004	0.28
Emergency	0.072	0.71
Grocery	3.084	9.83
Perishables	0.807	2.89
Household-Day Observations		25,939,400
Panel B: Purchase Statistics Conditional on Non-zero		
No. of Trips	1.57	0.98
Total Expenditure	22.47	27.92
Expenditure on Category		
Avoidance	6.67	9.44
Emergency	2.99	3.46
Grocery	14.41	16.98
Perishables	5.31	5.59
No. of Household-Day Obs.		6,682,988

Notes: Expenditures are expressed in 1980-82 US dollars. For each category of good, the sample consists of households who purchase a good from that category at some point during the sample years. Therefore, the conditional expenditure statistics in Panel B do not include households who never purchased a good from each respective category over the sample and the sum of the mean conditional expenditure by category is larger than mean total expenditure.

Table 3: Summary Statistics for Household Demographics

Variable	Full Sample	Treated Sub-sample: Fire	Treated Sub-sample: Fire 50mi	Treated Sub-sample: Smoke	Ailment Sample
Household Income	31272	27542	29737	31710	28652
	(17972)	(16652)	(17151)	(19188)	(14,678)
Household Size	2.371	2.513	2.471	2.353	2.153
	(1.332)	(1.371)	(1.383)	(1.314)	(1.214)
Married (=1)	0.591	0.674	0.624	0.597	0.570
	(0.492)	(0.469)	(0.484)	(0.491)	(0.495)
Age	57.90	57.69	57.73	58.58	61.03
	(13.51)	(13.89)	(13.57)	(13.82)	(12.95)
Education					
Grade School (=1)	0.00188	0.000768	0.00145	0.00299	0.00154
	(0.0433)	(0.0277)	(0.0380)	(0.0546)	(0.0393)
Some High School (=1)	0.0093	0.00768	0.00923	0.0103	0.00991
	(0.096)	(0.0873)	(0.0956)	(0.101)	(0.0991)
High School Grad (=1)	0.0989	0.122	0.110	0.104	0.101
	(0.299)	(0.327)	(0.313)	(0.305)	(0.301)
Some College (=1)	0.300	0.373	0.325	0.309	0.289
	(0.458)	(0.484)	(0.468)	(0.462)	(0.453)
College Grad (=1)	0.383	0.343	0.370	0.373	0.382
	(0.486)	(0.475)	(0.483)	(0.484)	(0.486)
Post College Grad (=1)	0.207	0.153	0.183	0.201	0.217
	(0.405)	(0.360)	(0.387)	(0.401)	(0.412)
Race					
White (=1)	0.680	0.768	0.713	0.699	0.705
	(0.466)	(0.422)	(0.452)	(0.459)	(0.456)
Black (=1)	0.0901	0.0561	0.0797	0.0733	0.0849
	(0.286)	(0.230)	(0.271)	(0.261)	(0.279)
Asian (=1)	0.126	0.0611	0.0961	0.126	0.127
	(0.332)	(0.240)	(0.295)	(0.332)	(0.333)
Other (=1)	0.103	0.114	0.111	0.102	0.0837
	(0.304)	(0.318)	(0.314)	(0.302)	(0.277)
Poverty (=1)	0.214	0.303	0.254	0.217	0.240
	(0.410)	(0.460)	(0.436)	(0.412)	0.427
Age Vulnerable (=1)	0.259	0.292	0.272	0.267	0.231
	(0.438)	(0.455)	(0.445)	(0.443)	0.422
Having Ailments (=1)					0.759
					(0.427)
No. of Observations	71,755	2,603	20,052	8,374	21,999
No. of Households	15,785	621	4378	1,664	6,763
No. of Years	14	14	14	14	8

Notes: Reported are the means with the standard deviations in the parentheses. Household income is expressed in 1980-82 US dollars. The first treated group experienced at least one fire within their zip area of residence in a year; the second experienced at least one fire within 50 miles of their zip area in a year; the third was exposed to wildfire smoke (PM2.5 above 35µg/m3) at least once in a year. Vulnerable age indicates age below 6 or above 64.

Table 4: Contemporaneous Effect on Retail Trips and Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fire				Smoke		
	1(Fire)	1(Fire 30mi)	1(Fire 50mi)	1(Fire 100mi)	1(Smoke)	Total Hours	PM2.5
Panel A: Trips							
Treatment	-0.00924	-0.00279	-0.000808	-0.000689	-0.0017	-0.000551	-0.000774
	(0.0126)	(0.00579)	(0.00622)	(0.00527)	(0.0025)	(0.00068)	(0.00511)
Trips Last Week	0.0619***	0.0619***	0.0619***	0.0619***	0.0619***	0.0619***	0.0619***
	(0.00088)	(0.00088)	(0.00088)	(0.00088)	(0.00088)	(0.00088)	(0.00088)
EPA PM2.5	7.93E-06	7.96E-06	7.92E-06	7.92E-06	8.70E-06	8.81E-06	9.72E-06
	(0.000037)	(0.000037)	(0.000037)	(0.000037)	(0.000037)	(0.000037)	(0.000038)
Observations	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.049	0.049	0.049	0.049	0.049
Panel B: Expenditures							
Treatment	-0.237	-0.138**	-0.0689	-0.0336	0.0787*	0.00939	0.301***
	(0.208)	(0.064)	(0.0919)	(0.0838)	(0.0465)	(0.0116)	(0.105)
Expenditures Last Week	0.0240***	0.0240***	0.0240***	0.0240***	0.0240***	0.0240***	0.0240***
	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)	(0.00126)
EPA PM2.5	0.000472	0.000475	0.000474	0.000472	0.000434	0.000456	-0.000237
	(0.000788)	(0.000788)	(0.000789)	(0.000789)	(0.000794)	(0.000789)	(0.000831)
Observations	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.016	0.016	0.016	0.016	0.016	0.016	0.016

Notes: The outcome is the daily number of trips to retail stores of a household in Panel A and daily retail expenditure in Panel B. The treatment is a binary indicator for whether there is a fire in the zip code area, within 30 miles, within 50 miles, and within 100 miles on that day in Columns 1-4, a binary indicator for smoke in Column 5, the number of hours smoke lasted in a day in Column 6, and the predicted PM2.5 concentration divided by 100 in Column 7. Standard errors clustered at the county level are in parentheses. Controls include household income, household size, marital status, age, education, race, daily mean (EPA-measured) PM2.5 concentration, day of the week, month, year, and county fixed effects. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 5: Contemporaneous Effects on Trips and Expenditure, Fire and Smoke Interacted

	(1)	(2)	(3)	(4)
	Trips		Expenditures	
	1(Fire)	1(Fire 50mi)	1(Fire)	1(Fire 50mi)
Fire	0.000316	-0.00794	-0.0669	-0.177
	(0.00635)	(0.0126)	(0.092)	(0.207)
PM2.5	-0.000274	-0.00692	0.303***	0.304***
	(0.0051)	(0.0051)	(0.105)	(0.105)
Fire×PM2.5	-0.0718	-0.0626	-0.260	-3.04*
	(0.0518)	(0.0881)	(1.01)	(1.67)
Observations	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.016	0.016
Effect of Smoke w/ Fire Present	-0.0721	-0.0633	0.0431	-2.74
	(0.0513)	(0.0870)	(1.00)	(1.67)

Notes: The outcome is the daily number of trips to retail stores of a household in Columns 1-2 and daily retail expenditure in Columns 3-4. Standard errors clustered at the county level are in parentheses. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Contemporaneous Effects on Purchases

	(1)	(2)	(3)	(4)
	Avoidance	Emergency	Grocery	Perishables
1(Fire)	-0.00362***	-0.001	-0.148	-0.063
	(0.000)	(0.011)	(0.111)	(0.045)
1(Fire 30mi)	0.002	-0.00837**	-0.079	-0.022
	(0.002)	(0.004)	(0.056)	(0.014)
1(Fire 50mi)	4.99e-05	-0.00896***	-0.052	-0.012
	(0.001)	(0.003)	(0.040)	(0.010)
1(Fire 100mi)	0.000	-0.00738***	-0.052	-0.012
	(0.001)	(0.002)	(0.044)	(0.012)
PM 2.5	0.0132***	0.000	0.230***	0.0905***
	(0.003)	(0.004)	(0.067)	(0.020)

Notes: Each coefficient is estimated in a separate regression. The treatment is a binary indicator for whether there is a fire that burned more than 1 acre in the zip code area, within 30 miles, within 50 miles, or within 100 miles or the predicted PM2.5 concentration divided by 100. The dependent variable is daily household expenditure on the respective category of goods. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total expenditure. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 23,856,038 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 7: Contemporaneous Effects by Fire and Smoke by Experience

	(1)	(2)	(3)	(4)	(5)	(6)
	Trips			Expenditures		
	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5
Panel A: Experience of Fire w/in 50 Miles						
Treatment	0.0601**	0.00488	0.00165	0.494	0.0716	0.326***
	(0.0284)	(0.0114)	(0.00576)	(0.449)	(0.154)	(0.118)
Treatment×1(Experience)	-0.0876***	-0.00886	-0.0119	-0.918	-0.219	-0.125
	(0.030)	(0.0117)	(0.0135)	(0.613)	(0.146)	(0.243)
1(Experience)	-0.00121	-0.0012	-0.00118	-0.0291	-0.0288	-0.0288
	(0.00337)	(0.00339)	(0.00339)	(0.0505)	(0.0507)	(0.0508)
Observations	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.049	0.016	0.016	0.016
Effect on HH w/ Experience	-0.0275***	-0.00398	-0.0102	-0.424	-0.148*	0.201
	(0.0107)	(0.00553)	(0.0118)	(0.262)	(0.0806)	(0.216)
Panel B: Experience of PM2.5>35µg						
Treatment	-0.00925	-0.00067	-0.0104	-0.181	-0.0509	0.169
	(0.0136)	(0.00639)	(0.00647)	(0.211)	(0.0993)	(0.136)
Treatment×1(Experience)	-8.27E-05	-0.00228	0.0267**	-0.636	-0.261	0.347*
	(0.0373)	(0.0221)	(0.0116)	(0.861)	(0.385)	(0.193)
1(Experience)	-0.000606	-0.000603	-0.000836	0.101	0.102	0.098
	(0.00308)	(0.00309)	(0.00308)	(0.0878)	(0.0879)	(0.0883)
Observations	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.049	0.016	0.016	0.016
Effect on HH w/ Experience	-0.00933	-0.00295	0.0163**	-0.816	-0.312	0.516***
	(0.0343)	(0.0217)	(0.00822)	(0.864)	(0.362)	(0.135)

Notes: The outcome is the daily number of trips to retail stores of a household in Columns 1-3 and daily retail expenditure in Columns 4-6. Standard errors clustered at the county level are in parentheses. PM2.5 is divided by 100. Other controls include day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures. * p<0.10, ** p<0.05, *** p<0.01. 23,875,021 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 8: Contemporaneous Effects on Purchases by Fire and Smoke Experience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Avoidance			Emergency			Grocery			Perishables		
	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5
Panel A: Experience of Fire w/in 50 Miles												
Treatment	-0.00377***	0.003	0.0135***	-0.005	-0.006	-0.006	-0.236	-0.085	0.255***	-0.114	-0.017	0.0976***
	(0.000)	(0.004)	(0.003)	(0.030)	(0.007)	(0.004)	(0.303)	(0.071)	(0.064)	(0.110)	(0.019)	(0.020)
Interaction	0.000	-0.004	-0.001	0.005	-0.005	0.0257**	0.120	0.060	-0.128	0.067	0.008	-0.035
	(0.000)	(0.004)	(0.006)	(0.032)	(0.007)	(0.012)	(0.412)	(0.089)	(0.151)	(0.149)	(0.023)	(0.045)
1(Experience)	0.000	0.000	0.000	0.000	0.000	0.000	-0.029	-0.029	-0.029	-0.006	-0.006	-0.006
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.031)	(0.031)	(0.031)	(0.008)	(0.008)	(0.008)
Panel B: Experience of PM2.5>35µg												
Treatment	-0.00357***	0.000	0.0133***	-0.002	-0.00862**	0.002	-0.068	-0.036	0.100	-0.033	-0.013	0.0541**
	(0.000)	(0.001)	(0.004)	(0.013)	(0.004)	(0.006)	(0.124)	(0.042)	(0.075)	(0.048)	(0.010)	(0.024)
Interaction	-0.001	-0.00444***	0.000	0.006	-0.005	-0.005	-0.920**	-0.230	0.340***	-0.336***	0.010	0.0950***
	(0.000)	(0.002)	(0.005)	(0.041)	(0.011)	(0.008)	(0.359)	(0.180)	(0.099)	(0.117)	(0.062)	(0.031)
1(Experience)	0.000	0.000	0.000	0.002	0.002	0.002	0.0906***	0.0907***	0.0873**	0.0285***	0.0285***	0.0275***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.034)	(0.034)	(0.034)	(0.008)	(0.008)	(0.008)

Notes: Interaction refers to the interaction between Treatment and Experience. In Panel A, experience is defined as a household living in a zip code that was within 50 miles of a fire the prior year. In Panel B, experience is defined as having experienced at least one day with wildfire-driven PM 2.5 exceeding 35µg/m^3. The dependent variable is daily household expenditure on the respective category of goods. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity), prior 7-day total expenditure, and experience. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 23,856,038 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 9: Contemporaneous Effects on Trips and Expenditures by Poverty Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Trips			Expenditures		
	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5
Treatment	-0.0247*	-0.00616	0.00449	-0.725***	-0.170**	0.352***
	(0.0145)	(0.00661)	(0.0063)	(0.196)	(0.077)	(0.119)
Treatment×1(Poverty)	0.0501	0.0198**	-0.0213	1.588***	0.375*	-0.207
	(0.0305)	(0.00923)	(0.0173)	(0.545)	(0.190)	(0.247)
1(Poverty)	0.00497	0.00495	0.00507	-0.226***	-0.226***	-0.224***
	(0.00491)	(0.00491)	(0.00494)	(0.0827)	(0.0825)	(0.0829)
Observations	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.049	0.017	0.017	0.017
Effect on HH in Poverty	0.0254	0.0137	-0.0168	0.862*	0.205	0.145
	(0.0253)	(0.0088)	(0.0143)	(0.477)	(0.203)	(0.217)

Notes: The outcome is the daily number of trips to retail stores of a household in Columns 1-3 and daily retail expenditure in Columns 4-6. Standard errors clustered at the county level are in parentheses. PM2.5 is divided by 100. Other controls include day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures. * p<0.10, ** p<0.05, *** p<0.01. 23,875,021 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 10: Contemporaneous Effects on Purchases by Poverty Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Avoidance			Emergency			Grocery			Perishables		
1(Fire)	-0.00396***			-0.007			-0.290***			-0.122***		
	(0.000)			(0.016)			(0.103)			(0.040)		
1(Fire 50mi)		-0.001			-0.0103*			-0.0715*			-0.0371***	
		(0.001)			(0.005)			(0.037)			(0.013)	
PM 2.5			0.0169***			0.002			0.355***			0.130***
			(0.004)			(0.004)			(0.084)			(0.024)
Treatment×1(Poverty)	0.00111***	0.002	-0.0149***	0.019	0.005	-0.008	0.460**	0.072	-0.503***	0.190**	0.0923***	-0.160***
	(0.000)	(0.004)	(0.005)	(0.032)	(0.010)	(0.009)	(0.202)	(0.087)	(0.178)	(0.079)	(0.026)	(0.044)

Notes: Treatment refers to the relevant fire or smoke treatment, i.e., 1(Fire 50mi), 1(Fire), or PM 2.5. Poverty is an indicator equal to one if a household's income is at or below the poverty line taking into account household size, as defined according to the federal government (see https://aspe.hhs.gov/topics/poverty-economic-mobility/poverty-guidelines/prior-hhs-poverty-guidelines-federal-register-references). The dependent variable is daily household expenditure on the respective category of goods. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity), prior 7-day total expenditure, and the poverty indicator. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 23,856,037 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 11: Contemporaneous Effects on Trips and Expenditures by Age Range

	(1)	(2)	(3)	(4)	(5)	(6)
	Trips			Expenditures		
	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5
Treatment	0.00671	0.000593	0.0183**	0.481	0.00683	0.536***
	(0.0231)	(0.0106)	(0.0075)	(0.452)	(0.181)	(0.146)
Treatment×1(Age Vulnerable)	0.00188	-0.00199	-0.0213	-2.051**	-0.547***	-0.429
	(0.0641)	(0.012)	(0.0187)	(0.952)	(0.163)	(0.360)
1(Age Vulnerable)	0.00284	0.00284	0.00292	-0.0467	-0.0463	-0.0454
	(0.00438)	(0.00438)	(0.00439)	(0.0912)	(0.0912)	(0.0915)
Observations	9,749,924	9,749,924	9,749,924	9,749,924	9,749,924	9,749,924
R-squared	0.056	0.056	0.056	0.016	0.016	0.016
Effect on HH in Vulnerable Age Range	0.00859	-0.0014	-0.003	-1.571***	-0.540***	0.107
	(0.0543)	(0.0184)	(0.0173)	(0.604)	(0.190)	(0.311)

Notes: The outcome is the daily number of trips to retail stores of a household in Columns 1-3 and daily retail expenditure in Columns 4-6. Standard errors clustered at the county level are in parentheses. PM2.5 is divided by 100. Other controls include day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures. * p<0.10, ** p<0.05, *** p<0.01. 23,875,021 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 12: Contemporaneous Effects on Purchases by Age Range

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Avoidance			Emergency			Grocery			Perishables		
1(Fire)	-0.00299***			0.029			0.323			0.021		
	(0.000)			(0.030)			(0.230)			(0.091)		
1(Fire 50mi)		0.000			-0.006			0.016			-0.012	
		(0.001)			(0.011)			(0.076)			(0.019)	
PM 2.5			0.0118**			0.0152*			0.482***			$\underline{0.0974^{***}}$
			(0.005)			(0.008)			(0.104)			(0.036)
Treatment×1(Age Vulnerable)	0.000	$\underline{-0.00261^{***}}$	-0.005	$\underline{-0.0759^{**}}$	-0.024	-0.019	-1.171**	$\underline{\underline{-0.357^{***}}}$	-0.863***	$\underline{\underline{\underline{-0.245^{*}}}}$	-0.039	-0.047
	(0.000)	(0.001)	(0.008)	(0.033)	(0.017)	(0.014)	(0.457)	(0.117)	(0.243)	(0.126)	(0.057)	(0.073)

Notes: Treatment refers to the relevant fire or smoke treatment, i.e., 1(Fire 50mi), 1(Fire), or PM 2.5. Age Vulnerable is an indicator equal to one if at least one household member is five years old or less or sixty-five years old or more. The dependent variable is daily household expenditure on the respective category of goods. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity), prior 7-day total expenditure, and the age vulnerable indicator. Standard errors in parentheses are clustered at the county level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. 9,746,675 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Table 13: Contemporaneous Effects on Trips and Expenditures by Ailment Status

	(1)	(2)	(3)	(4)	(5)	(6)
	Trips			Expenditures		
	1(Fire)	1(Fire 50mi)	PM2.5	1(Fire)	1(Fire 50mi)	PM2.5
Treatment	-0.0431	-0.00853	0.00823	-0.633	-0.0505	0.262
	(0.0334)	(0.0161)	(0.0144)	(0.591)	(0.241)	(0.296)
Treatment×1(Ailments)	0.0887	0.0196	-0.0139	1.15	0.00436	-0.0410
	(0.0650)	(0.0261)	(0.0159)	(1.182)	(0.373)	(0.391)
1(Ailments)	0.0161***	0.0161***	0.0162***	0.426***	0.427***	0.427***
	(0.00419)	(0.00418)	(0.0042)	(0.0822)	(0.0821)	(0.0822)
Observations	7,699,984	7,699,984	7,699,984	7,699,984	7,699,984	7,699,984
R-squared	0.053	0.053	0.053	0.016	0.016	0.016
Effect on HH w/ Ailments	0.0456	0.011	-0.0057	0.517	-0.0461	0.221
	(0.0409)	(0.0119)	(0.0106)	(0.823)	(0.196)	(0.234)

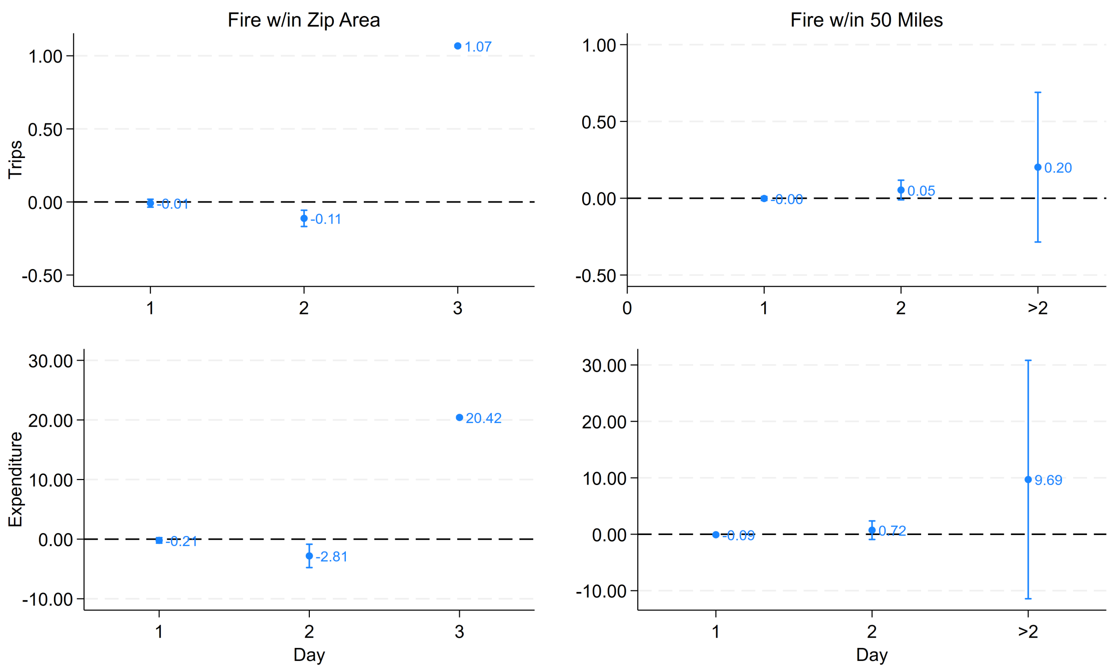
Notes: The outcome is the daily number of trips to retail stores of a household in Columns 1-3 and daily retail expenditure in Columns 4-6. Standard errors clustered at the county level are in parentheses. PM2.5 is divided by 100. Other controls include day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures. * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Contemporaneous Effects on Purchases by Ailment Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Avoidance			Emergency			Grocery			Perishables		
1(Fire)	-0.00393***			-0.0344*			-0.102			0.041		
	(0.001)			(0.018)			(0.346)			(0.149)		
1(Fire 50mi)		-0.001			-0.0149***			-0.237			-0.048	
		(0.002)			(0.005)			(0.171)			(0.064)	
PM 2.5			0.006			-0.016			-0.163			0.044
			(0.005)			(0.011)			(0.178)			(0.067)
Treatment×1(Ailment)	0.000	-0.002	0.005	0.0417*	0.004	0.007	0.235	0.236	0.567**	-0.048	0.062	0.090
	(0.000)	(0.002)	(0.004)	(0.024)	(0.007)	(0.012)	(0.534)	(0.221)	(0.247)	(0.214)	(0.071)	(0.098)

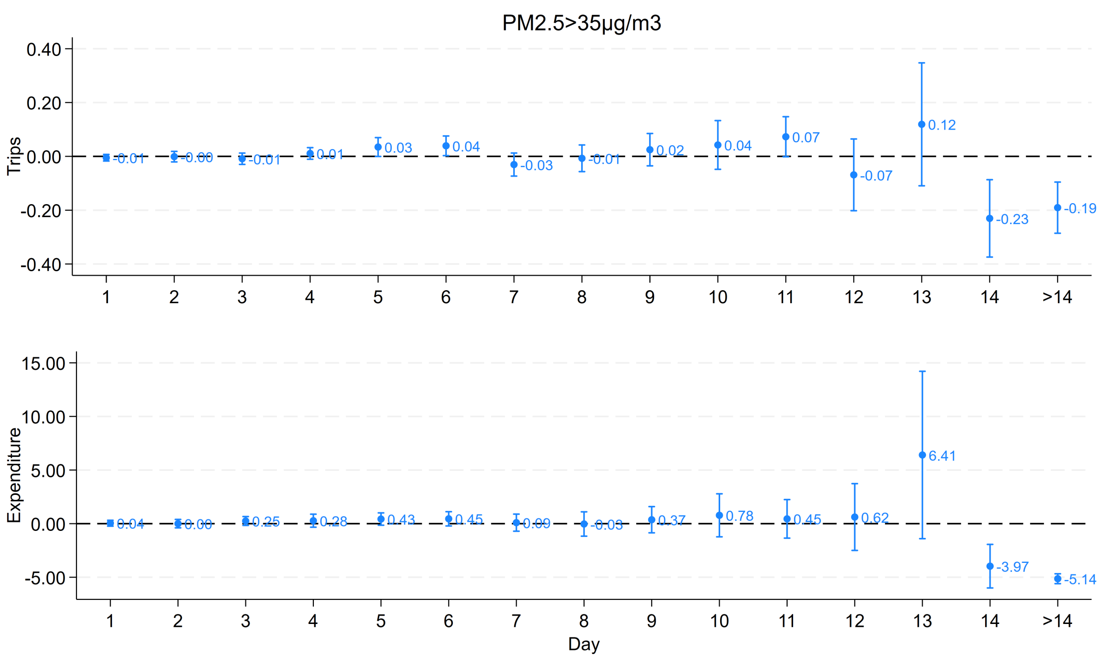
Notes: Treatment refers to the relevant fire or smoke treatment, i.e., 1(Fire 50mi), 1(Fire), or PM 2.5. Ailment is an indicator equal to one if at least one person in the household reported experiencing in the prior year one of the ailments listed in Table A1. The dependent variable is daily household expenditure on the respective category of goods. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity), prior 7-day total expenditure, and the ailment indicator. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 7,691,773 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline under a coefficient denotes cases where the coefficient's significance decreases by two categories (i.e., loses two significance stars). A triple underline denotes loss of statistical significance after the correction.

Figure 1: Cumulative Effects of Wildfires



Notes: Bars stand for the 95% confidence intervals. The outcome on the top is the daily number of retail trips and the outcome on the bottom is daily total retail expenditure. The treatment is a binary indicator for the i^{th} day of having a fire within a household's zip code on the left and within 50 miles on the right. Robust standard errors are clustered at the county level. Regressions control for day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures.

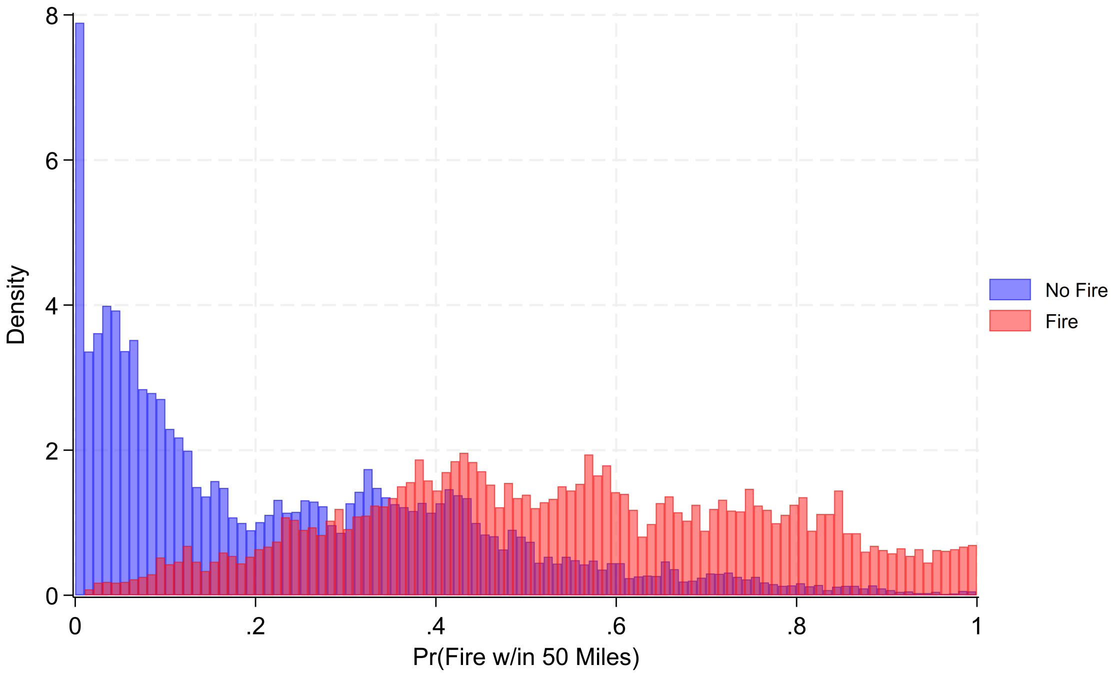
Figure 2: Cumulative Effects of Wildfire Smoke



Notes: Bars stand for the 95% confidence intervals. The outcome on the top is the daily number of retail trips and the outcome on the bottom is daily total retail expenditure. The treatment is a binary indicator for the i^{th} day of experiencing wildfire-driven PM2.5 greater than $35\mu g/m^3$ within household's zip code. Robust standard errors are clustered at the county level. Regressions control for day of the week, month, year, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total trips or expenditures.

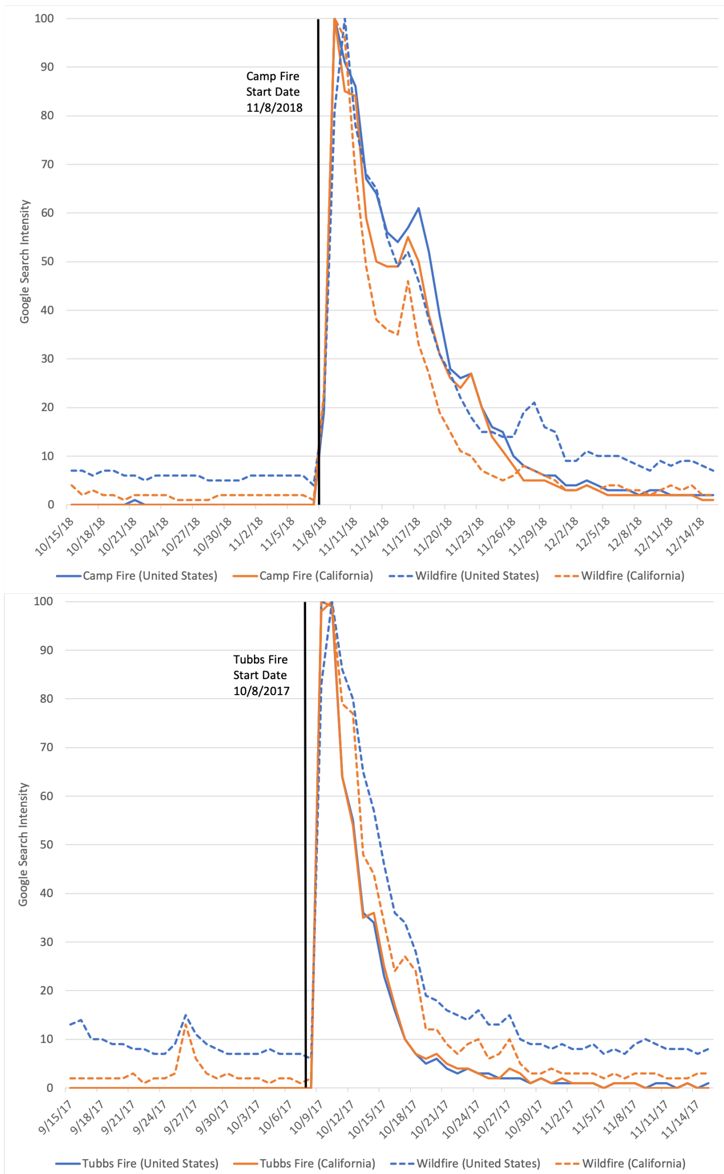
A Appendix

Figure A1: Propensity Score Distribution



Notes: The propensity score to to have one or more wildfires within 50 miles from the centroid of a zip code area in a year is estimated using a Probit model. Regressors include the latitude and longitude of the zip code area centroid, as well as their quadratic terms, of each zip area, the distance to the ocean and its square, elevation and its square, share of water body, climate zone, and year fixed effects.

Figure A1: Google Search Trends for California's Tubbs and Camp Wildfires



Notes: Google search intensity data comes from trends.google.com. Intensity is a normalized value created by Google (based on search volume) with 0 indicating no interest and 100 indicating maximum interest. Here we show search intensity for the terms "Camp Fire," "Tubbs Fire," and "Wildfire" based on both US-wide and California-specific searches for approximately a month around the start date of the fires. The Camp Fire, California's most deadly wildfire, lasted from 11/8/2018 - 11/25/2018. The Tubbs Fire, California's most destructive wildfire at the time, lasted from 10/8/2017 - 10/31/2017. Not only do searches for the named fires only begin after the start of the fire, but there is no uptick in searches for "wildfire" in the days prior to the start of the fire. We interpret this as anecdotal evidence of lack of awareness about the impending wildfires.

Table A1: List of Ailments

1	Acne
2	Allergies (outdoor, hay fever, indoor, seasonal, etc.)
3	Anxiety/Depression
4	Asthma
5	Chronic Bronchitis/Pulmonary Disease/COPD/Emphysema
6	Cancer
7	Pre-Diabetes
8	Diabetes - Type I
9	Diabetes - Type II
10	Dry Eye (loss or reduction of ability to produce tears)
11	Eye Disease (Glaucoma, Cataracts, Macular Degeneration, etc.)
12	Headache - chronic/tension
13	Headache - migraine
14	Heart Disease / Heart Attack / Angina / Heart Failure
15	High Blood Pressure / Hypertension
16	Skin Condition - not acne (Skin Rash / Irritation / Eczema / Dermatitis, etc., excluding Psoriasis)

Table A2: Contemporaneous Effect on Retail Trips and Expenditure, Propensity Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fire				Smoke		
	1(Fire)	1(Fire 30mi)	1(Fire 50mi)	1(Fire 100mi)	1(Smoke)	Total Hours	PM2.5
Panel A: Trips							
Treatment	-0.0128	-0.00444	-0.00155	-0.00116	-0.00326	-0.000833	-0.00421
	(0.0117)	(0.00554)	(0.00594)	(0.00505)	(0.00286)	(0.000733)	(0.006150)
Trips Last Week	0.0627***	0.0627***	0.0627***	0.0627***	0.0627***	0.0627***	0.0627***
	(0.000724)	(0.000724)	(0.000724)	(0.000724)	(0.000724)	(0.000724)	(0.000724)
EPA PM2.5	1.37e-05	1.38e-05	1.37e-05	1.37e-05	1.53e-05	1.52e-05	2.31e-05
	(0.000049)	(0.000049)	(0.000049)	(0.000049)	(0.000049)	(0.000049)	(0.000050)
Observations	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367
R-squared	0.050	0.050	0.050	0.050	0.050	0.050	0.050
Panel B: Expenditures							
Treatment	-0.293	-0.154**	-0.0744	-0.0372	0.084	0.00989	0.228**
	(0.198)	(0.0603)	(0.0869)	(0.0801)	(0.0541)	(0.0137)	(0.109)
Expenditures Last Week	0.0244***	0.0244***	0.0244***	0.0244***	0.0244***	0.0244***	0.0244***
	(0.00139)	(0.00139)	(0.00139)	(0.00139)	(0.00139)	(0.00139)	(0.00139)
EPA PM2.5	-0.000146	-0.000143	-0.000145	-0.000146	-0.000189	-0.000166	-0.000656
	(0.00104)	(0.00104)	(0.00104)	(0.00104)	(0.00105)	(0.00104)	(0.00110)
Observations	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367	17,525,367
R-squared	0.016	0.016	0.016	0.016	0.016	0.016	0.016

Notes: Regressions are run on a sample trimmed based on the propensity score to have a fire within 50 miles that is between 0.1 and 0.9. The outcome is the daily number of trips to retail stores of a household in Panel A and daily retail expenditure in Panel B. The treatment is a binary indicator for whether there is a fire in the zip code area, within 30 miles, within 50 miles, and within 100 miles on that day in Columns 1-4, a binary indicator for smoke in Column 5, the number of hours smoke lasted in a day in Column 6, and the predicted PM2.5 concentration divided by 100 in Column 7. Standard errors clustered at the county level are in parentheses. Controls include household income, household size, marital status, age, education, race, daily mean (EPA-measured) PM2.5 concentration, day of the week, month, year, and county fixed effects. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A3: Contemporaneous Effects on Retail Trips and Expenditure, 10-acre Wildfires

	(1)	(2)	(3)	(4)
	1(Fire)	1(Fire 30mi)	1(Fire 50mi)	1(Fire 100mi)
Panel A: Trips				
Treatment	-0.0065	-0.00569	-0.00267	-0.000476
	(0.0163)	(0.00668)	(0.00464)	(0.00387)
Trips Last Week	0.0619***	0.0619***	0.0619***	0.0619***
	(0.00088)	(0.00088)	(0.00088)	(0.00088)
EPA PM2.5	7.92E-06	8.00E-06	7.95E-06	7.91E-06
	(0.000037)	(0.000037)	(0.000037)	(0.000037)
Observations	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.049	0.049	0.049	0.049
Panel B: Expenditures				
Treatment	-0.406	-0.165	-0.0604	0.0307
	(0.261)	(0.0988)	(0.0772)	(0.0730)
Expenditures Last Week	0.0240***	0.0240***	0.0240***	0.0240***
	(0.00126)	(0.00126)	(0.00126)	(0.00126)
EPA PM2.5	0.000473	0.000474	0.000473	0.000471
	(0.000788)	(0.00079)	(0.000788)	(0.000789)
Observations	23,875,021	23,875,021	23,875,021	23,875,021
R-squared	0.016	0.016	0.016	0.016

Notes: Each coefficient is estimated in a separate regression. The treatment is a binary indicator for whether there is a fire that burned more than 10 acres in the zip code area, within 30 miles, within 50 miles, or within 100 miles. The dependent variable is daily household expenditure on the respective category of goods. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total expenditure. Standard errors in parentheses are clustered at the county level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Contemporaneous Effects on Purchases, 10-acre Wildfires

	(1)	(2)	(3)	(4)
	Avoidance	Emergency	Grocery	Perishables
1(Fire)	-0.00364***	0.006	-0.179	-0.091
	(0.000)	(0.014)	(0.239)	(0.065)
1(Fire 30mi)	0.004	-0.007	-0.102	-0.013
	(0.003)	(0.005)	(0.071)	(0.035)
1(Fire 50mi)	0.001	-0.006	-0.053	-0.010
	(0.002)	(0.004)	(0.044)	(0.020)
1(Fire 100mi)	0.001	$\underline{\underline{\text{-0.00415}}}$*	-0.035	-0.009
	(0.002)	(0.002)	(0.044)	(0.018)

Notes: Each coefficient is estimated in a separate regression. The treatment is a binary indicator for whether there is a fire that burned more than 10 acres in the zip code area, within 30 miles, within 50 miles, or within 100 miles. The dependent variable is daily household expenditure on the respective category of goods. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total expenditure. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 23,856,038 observations per regression. A single underline under a coefficient denotes cases where the coefficient's significance decreases by one category after the Anderson (2008) correction (i.e., loses one significance star). A double underline denotes loss of statistical significance after the correction.

Table A5: Non-linear Effect of PM 2.5

	(1)	(2)
	Trips	Expenditures
1(12<PM2.5≤35)	-0.000926	0.074
	(0.00299)	(0.0697)
1(35<PM2.5≤55)	-0.00609	0.0229
	(0.00564)	(0.105)
1(55<PM2.5≤150)	0.00864	0.254*
	(0.00592)	(0.150)
1(PM2.5>150)	0.0132	0.933
	(0.0269)	(0.579)
EPA PM2.5	-1.68E-06	-0.000202
	(0.000039)	(0.000841)
Observations	23,875,021	23,875,021
R-squared	0.049	0.016
Joint F	0.848	2.415*

Notes: The outcome is the daily number of trips to retail stores of a household in Column 1 and daily retail expenditure in Column 2. Standard errors clustered at the county level are in parentheses. Controls include household income, household size, marital status, age, education, race, daily mean (EPA-measured) PM2.5 concentration, day of the week, month, year, and county fixed effects. * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Contemporaneous Effects on Quantities

	(1)
1(Fire)	-0.000843***
	(0.000)
1(Fire 30mi)	0.000
	(0.000)
1(Fire 50mi)	0.000
	(0.000)
1(Fire 100mi)	0.000
	(0.000)
PM 2.5	0.00251***
	(0.001)

Notes: Each coefficient is estimated in a separate regression. The dependent variable is daily household purchase count of the respective category of goods. PM2.5 is divided by 100. All regressions include year, month, day of week, and county fixed effects, as well as daily mean (EPA-measured) PM2.5 concentration and household characteristics (income, size, marital status, age, education, and race/ethnicity) and prior 7-day total purchase count. Standard errors in parentheses are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.1. 23,856,038 observations per regression.