# A Burning Issue: Wildfire Smoke Exposure, Retail Sales, and Demand for Adaptation in Healthcare

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## Abstract

Wildfire events have increased in frequency and severity across the United States in recent decades. While a growing literature has documented the effects of wildfire smoke exposure on a wide range of health and socioeconomic outcomes, little is known about its impact on consumer behavior and household demand for adaptation in healthcare. We combine a newly developed and digitized dataset on daily wildfire smoke PM2.5 concentrations across the contiguous United States from 2006 to 2019 with weekly NielsenIQ retail scanner data to quantify how wildfire smoke exposure affects retail sales of air purifiers, bottled water, cold remedies, nasal products, cough products, and nutritional products. We find a positive and statistically significant impact of wildfire smoke exposure on the retail sales of these products. Dynamic effects are evident as wildfire smoke exposure in previous weeks also increases current sales. Nonlinear effects arising from the varying intensity of wildfire smoke exposure also reveal distinct patterns of demand for adaptation. We further explore how the effects of wildfire smoke exposure vary with socio-demographic characteristics, focusing on social vulnerability and highlighting the implications of environmental justice. Our results underscore the need for proactive policies to address the increased demand for medical and healthcare products as household adaptive measures during the wildfire season, particularly targeting socioeconomically vulnerable populations who may be prone to limited access to preventive measures against wildfire smoke.



**Keywords**: wildfire smoke, PM2.5, adaptive measure, healthcare product, retail sales


**Disclaimers**: Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

## 1. Introduction

Wildfires, an increasingly prevalent phenomenon across the globe, impose significant health risks on individuals exposed to their smoke (Burke et al., 2021). Over the past decade, there has been a 27-fold increase in the number of people residing in areas where the annual wildfire smoke-driven PM2.5 level exceeds 100 $\mu g/m^3$ for at least one day. This included nearly 25 million individuals in the year 2020 alone (Childs et al., 2022). Data from the National Oceanic and Atmospheric Administration (NOAA) reveals that, from 1980 to 2023, the United States experienced over 20 billion-dollar wildfire events. Notably, 80% of these catastrophic wildfires have taken place since 2000 (NOAA, 2023). The financial toll has also been heavy. In recent decades, the United States has regularly expended over $1 billion annually in wildfire fighting efforts, culminating in a peak of $2.3 billion in 2020 (National Interagency Fire Center, 2022).

Wildfire smoke includes a wide variety of pollutants, such as greenhouse gases (carbon dioxide, methane, nitrous oxide), photochemically reactive compounds (e.g., carbon monoxide, nonmethane volatile organic carbon, nitrogen oxides), and particulate matter (Urbanski et al., 2008), which can lead to significant health effects and social costs. Such consequences span from reductions in birth weights (Holstius et al., 2012) to increased emergency department visits (Heft-Neal et al., 2023) and heightened rates of respiratory hospital admissions (Delfino et al., 2009). The health implications of wildfires may stimulate a rising demand for emergency supplies and adaptive healthcare products, such as filtration tools, hydration resources, and over-the-counter (OTC) medical products in fire-affected areas. Failure to secure these crucial supplies promptly can amplify health risks, potentially leading to severe respiratory conditions, chronic health problems, or even life-threatening situations among fire-affected populations.

This paper examines the contemporaneous and dynamic effects of wildfire smoke exposure on the retail sales of emergency supplies and adaptive healthcare products in the United States. We combine a newly developed and digitized dataset on daily wildfire smoke PM2.5 concentrations across the contiguous United States from 2006 to 2019 with weekly county-level NielsenIQ retail scanner data to quantify how wildfire smoke exposure affects retail sales of air purifiers, bottled water, cold remedies, nasal products, cough drops, and nutritional products. To do so, we first estimate the contemporaneous effects to establish whether wildfire exposure (measured as the number of smoke days per week and smoke-driven PM2.5 levels) influences the retail sales of these products. To allow for potential delayed responses to wildfire smoke exposure, we further explore the dynamic effects by using a distributed lag model that includes a lag of up to four weeks of wildfire smoke exposure. We also investigate the nonlinear effects ensuing from the varying intensity of wildfire smoke exposure. Finally, our exploration extends to the heterogeneity in treatment effects across different socio-demographic groups, leveraging county-level data from the Social Vulnerability Index (SVI) developed by the Centers for Disease Control and Prevention (CDC).

Our study has four primary results. First, there is a positive and statistically significant impact of wildfire smoke exposure on the retail sales of healthcare products. Specifically, an increase in wildfire smoke days per week leads to increased retail sales by 0.12%-0.97%, depending on the product. Notably, the top three products exhibiting the highest increases in retail sales are cold remedies, bottled water, and nasal products. Furthermore, one unit increase in weekly smoke-driven PM2.5 (1 $\mu g/m^3$) is associated with a significant increase in weekly sales of these products by 0.12%-1.56%. This rise is particularly pronounced for products directly associated with treating health conditions caused by wildfire smoke exposure.

Second, a distributed lag model allows us to investigate the potential dynamic relationship between wildfire smoke exposure and consumption behaviors, a crucial indicator of adaptative responses. Even with a lag of up to four weeks, we observe a persistently positive and statistically significant impact of the current week's wildfire smoke exposure on retail sales. When we focus on a one-week lag of exposure, we still find an increase in retail sales for most products, albeit to a lesser extent than the effects of the current week's exposure. These findings imply that the influence of wildfire smoke exposure on household consumption behaviors extends beyond the immediate aftermath, highlighting a prolonged effect.

Third, our nonlinear effects of wildfire smoke exposure on retail sales reveal several intriguing patterns, suggesting distinct demands for adaptation based on the severity of wildfire smoke exposure. We find that counties exposed to wildfire smoke for only one or two days per week have increased retail sales for cold remedies, cough drops, and nasal products, ranging from 0.74% to 3.6%. This suggests that individuals are more likely to purchase these products in response to mild wildfire smoke exposure, potentially to alleviate symptoms associated with respiratory conditions. Conversely, in counties exposed to six or seven days of wildfire smoke per week, we find considerable increases in retail sales of air purifiers, escalating by 45.5% and 66.9%

respectively. This points to significant demand for durable adaptative products such as air purifiers during periods of intense and prolonged wildfire smoke exposure.

Fourth, we delve into the potential heterogeneity of responses to wildfire smoke exposure using county characteristics, as households of varying socio-demographics may exhibit different levels of adaptive capacity and preferences during natural disasters or under conditions influenced by environmental pollution. We find several key findings: (1) counties with a higher proportion of uninsured and elderly residents show increased sales of healthcare products in response to wildfire smoke exposure, suggesting a dependency on retail-purchased medical items and an enhanced vulnerability, which may impose additional financial burdens; and (2) counties with a higher proportion of individuals lacking access to a vehicle or Black/African American residents tend to have lower retail sales, pointing to transportation constraints and potential access disparities, respectively, that may hinder effective responses to wildfire smoke exposure.

Our paper contributes to three different strands of literature. First, it builds on the growing literature that investigates a wide range of impacts of wildfire smoke exposure (Delfino et al., 2009; Holstius et al., 2012; Borgschulte et al., 2022; Burke et al., 2022; Gellman et al., 2022; Wen and Burke, 2022; Heft-Neal et al., 2023; Molitor et al., 2023; Walls and Wibbenmeyer, 2023). While the extant literature primarily estimates the impacts of wildfire smoke on health outcomes such as mortality, hospitalization, birth outcomes, and suicide deaths, economic outcomes like labor productivity and economic output, and cognitive outcomes including test scores and mental health, our study introduces a unique focus on retail sales of emergency supplies and adaptive healthcare products, the most commonly adopted measures by households facing wildfire smoke. Such an investigation not only brings a new perspective to existing research but also underscores the practicality of these measures as readily implementable strategies for policymakers to mitigate health risks associated with wildfire smoke.

Second, our heterogeneity analysis based on SVI aligns with the environmental justice component of pollution exposure and policy response. A breadth of interdisciplinary research substantiates that low-income households and people of color disproportionately grapple with air pollution exposure (Mohai et al., 2009; Banzhaf et al., 2019; Chakraborti and Shimshack, 2022). Additionally, individuals with the same environmental conditions may demonstrate varying health outcomes due to their differentiated engagement in protective and adaptive behaviors (Giaccherini et al., 2021). Specifically, higher-income individuals tend to take more preventive actions to avoid risk in comparison with those with lower incomes (Chen and Chen, 2020; Ito and Zhang, 2020). In the context of our study, even though the occurrence of wildfires is arguably exogenous, evidence suggests that wildfire risk mitigation efforts, such as federal wildfire fuel projects, are disproportionately implemented in communities that are wealthier, whiter, and more educated (Anderson et al., 2023). Moreover, wildfire containment strategies have been observed to favor wealthier neighborhoods (Plantinga et al., 2022). In contrast, households with lower incomes are less likely to remain indoors and own indoor pollution monitoring devices during extensive wildfire smoke events (Burke et al., 2022). Our focus on socioeconomically vulnerable communities, therefore, contributes to a deeper comprehension of social disparities in response to wildfire smoke exposure and highlights the importance of prioritizing government aid in vulnerable populations when mitigation efforts are insufficient in affected areas.

Lastly, this study uniquely contributes to the literature on various household responses to pollution, extreme weather events, and natural disasters. Previous research has mainly focused on increased household consumption in response to hurricanes (Sneath et al., 2009; Larson and Shin, 2018; Floyd and Ishdorj, 2022) and the COVID-19 pandemic (Dulam et al., 2021; Kar et al., 2022) and decreased consumption of groceries in the face of extreme heat (Lee and Zheng, 2022). Particularly, Beatty et al. (2019) find that sales of emergency supplies like bottled water, batteries, and flashlights increase when a location is threatened by a hurricane, with the bulk of the sales increase occurring immediately before forecasted landfall. In response to the threat of air pollution, individuals frequently adopt avoidance strategies, including the reduction of outdoor activities (Bresnahan et al., 1997; Zivin and Neidell, 2009; Janke, 2014; Liao et al., 2021). When circumstances necessitate outdoor exposure, they often opt for defensive measures, such as acquiring protective equipment like masks, air purifiers, medications, and health insurance, as a proactive approach to safeguarding their well-being from the adverse impacts of air pollution (Deschenes et al., 2017, Zhang and Mu, 2018; Chen and Chen, 2020; Ito and Zhang, 2020). Our study focuses on sales of medical and healthcare products, such as respiratory treatments and nutritional items – a domain that despite its economic relevance, remains underexplored in literature. These products, unlike daily necessities like groceries, are normally not purchased out of panic but represent measured, strategic responses to mitigate the health consequences of extreme weather events and natural disasters such as wildfires. This perspective broadens our understanding of household adaptive behavior under wildfire threats, presenting some new evidence that deviates from the conventional disaster response narrative.

## 2. Data

To explore the impact of wildfire smoke exposure on consumer behavior and demand for adaptation in medical healthcare products, we assemble a comprehensive dataset from four sources. The wildfire smoke data is obtained from Childs et al. (2022), which provides robust and reliable information on wildfire occurrences and extents across the contiguous United States. We match the wildfire smoke data with retail scanner data collected by the Nielsen Company (US), LLC, focusing on retail sales of multiple products that are considered to help households deal with (and adapt to) wildfire smoke exposure. To enhance our analysis and explore heterogeneity in responses to wildfire smoke exposure, we integrate socio-demographic data from the CDC and weather data from PRISM. Our data sample covers the contiguous United States from 2006 to 2019 at the county-week level. The following sections describe data construction in more detail.

### 2.1 Wildfire smoke data

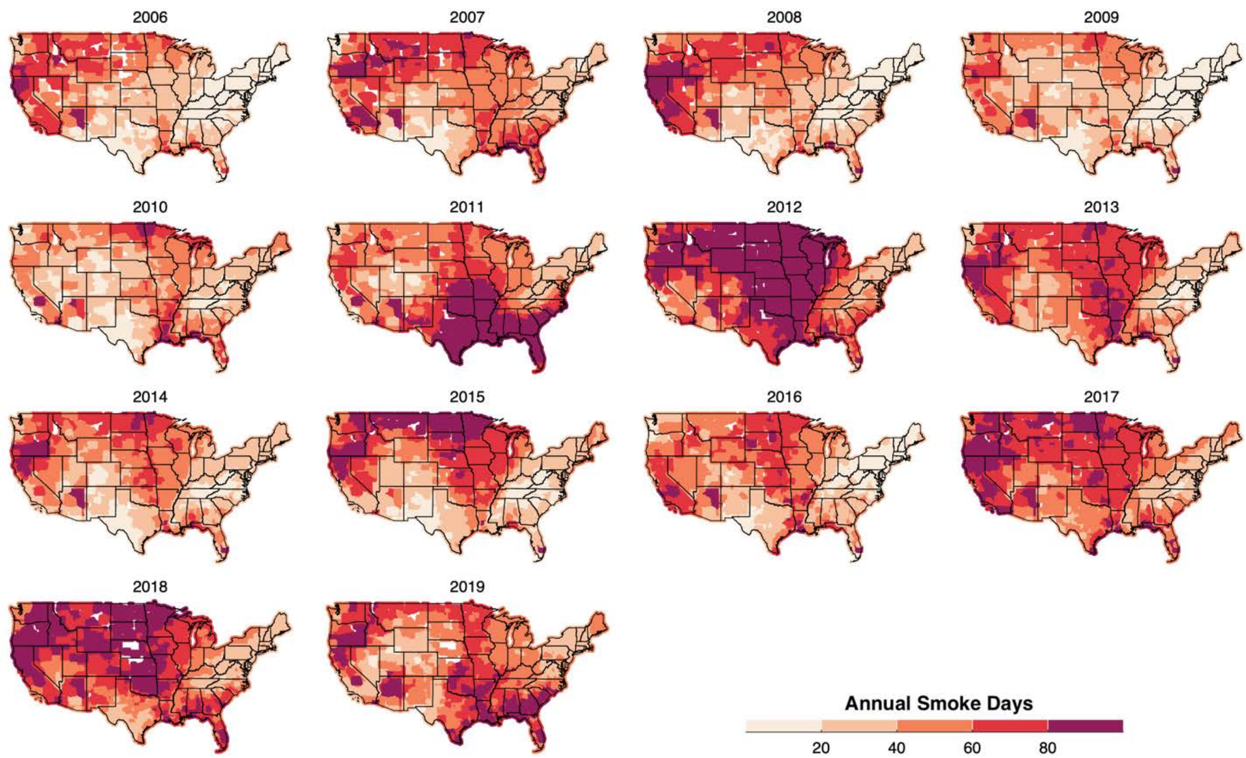
Childs et al. (2022) generated daily predictions of smoke-driven PM2.5 at a 10-km resolution across the contiguous United States from 2006 to 2020, which is the first and most precise and robust dataset on pollutant concentrations attributable to wildfire smoke.[1] They used the smoke plume data from the NOAA Hazard Mapping System to construct a binary classification of smoke days for each grid cell. A grid cell was classified as a smoke day if it had any intersection with a smoke plume. In cases where plume identification was hindered by cloud cover, air particle trajectory modeling from fire locations was used to aid in smoke identification. To define the time series of smoke-driven PM2.5 in each county, they combine the classification of smoke days with

[1] Most prior studies use daily smoke plumes produced by the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS) to explore the impacts of wildfire smoke exposure (e.g., Burkhardt et al., 2019; Miller et al., 2021; Borgschulte et al., 2022; Molitor et al., 2023). Nevertheless, it is important to acknowledge a limitation inherent to HMS due to its inability to distinguish wildfire smoke from smoke produced by controlled wildland burns, agricultural fires, or other sources (Brey and Fischer, 2016). Furthermore, the presence of cloud cover can obscure smoke plumes detected by HMS. In contrast, the dataset used in this paper is the daily predictions of smoke-driven PM2.5, which are generated through a robust machine learning model that leverages ground monitor data, HMS plume data, and reanalysis data sources (see Childs et al., 2022 for details). This innovative approach enhances the accuracy of the wildfire smoke exposure data.

daily average PM2.5 concentrations obtained from EPA monitoring stations and aggregate the smoke-driven PM2.5 predictions using population and area of intersection-weighted averaging.

Importantly, these estimates of smoke-driven PM2.5 are predictions made specifically for smoke days, based on which we can identify whether a county-day had smoke exposure. That is, if the smoke-driven PM2.5 concentration is non-zero in a county, it unequivocally indicates the presence of wildfire smoke exposure in that county. Note that there may be a case when a county-day did have wildfire smoke but did not experience elevated PM2.5 to be detected, leading to a smoke-driven PM2.5 prediction of 0. However, we find that in approximately 99.9% of the cases, when the smoke-driven PM2.5 is zero in a county, there is no wildfire smoke exposure. As a result, we can obtain a full set of smoke-driven PM2.5 predictions on both smoke days and non-smoke days. Figure 1 demonstrates the spatial and temporal distributions of annual smoke days across the contiguous United States spanning 2006-2019.

**Figure 1. Spatial and Temporal Distributions of Annual Smoke Days**




Note: This figure plots the number of days of each county exposed to wildfire smoke in each year during 2006-2019. The average number of wildfire smoke days is 47.05 days per year, ranging from 28.12 days (in 2006) to 58.75 days (in 2019).

## 2.2 NielsenIQ data

Retail sales data are sourced from the Nielsen Company (US), LLC's Scan Track supermarket scanner database and made available for research purposes by the Kilts Marketing Data Center at the University of Chicago Booth School of Business. This dataset covers over 3 million universal product codes (UPCs) collected from over 35,000 participating stores across the United States. Each store provides weekly retail sales data for every UPC that had any sales volume during the week. This dataset effectively eliminates biases related to strategic decisions, recall limitations, and observer biases. Consequently, this dataset provides a reliable reflection of actual consumer purchasing behavior and offers a precise representation of market dynamics.[2]

The scope of our study includes a broad array of items, ranging from air purifiers, bottled water, adult and children's cold remedies, cough drops, nasal products, and sinus remedies, to complete nutritional products and supplements. The retail sales of these items provide a clear representation of household adaptive measures to wildfire smoke exposure, seeking to alleviate symptoms such as respiratory issues or nasal discomfort (Reid et al., 2016; Xu et al., 2020). Particularly, we include bottled water, not only as a common remedy advised by experts to ease symptoms like scratchy throat and coughing due to smoke exposure but also as a safe drinking alternative in fire-affected areas. This is especially crucial as local water supplies may be contaminated during and after wildfire events (Stone et al., 2019; Proctor et al., 2020). The retail sales of these items thus offer tangible insights into the public's proactive strategies to mitigate health concerns tied to wildfire smoke exposure.

Our final dataset covers the period of 2006-2019 and includes retail sales data from 2,761 counties over 730 weeks, spanning from January to December. The dataset comprises a total of 2,015,530 county-week observations. To ensure data integrity, we exclude counties with no sales

[2] In this study, we use NielsenIQ Retailer Scanner Data instead of NielsenIQ Consumer Panel Data for two primary reasons. First, although the Consumer Panel Data comprises a representative panel of households that consistently provide information about their purchases, the geographical coverage of participating households is not as extensive as that in the Retailer Scanner Data. Consequently, the spatial distribution of household locations in the Consumer Panel Data is not directly comparable to the spatial distribution of wildfire events. Second, the number of observations within the Consumer Panel Data is rather limited, making it inadequate for our specific objective of estimating the impacts of wildfire smoke exposure.

for the entire year, considering these instances missing data rather than true zeros.[3] As a result, we have 1,853,441 county-week observations. Among these, 312 county-week observations lack data on temperature or precipitation. Hence, the total number of observations included in the empirical analysis amounts to 1,853,129.

### 2.3 Weather data

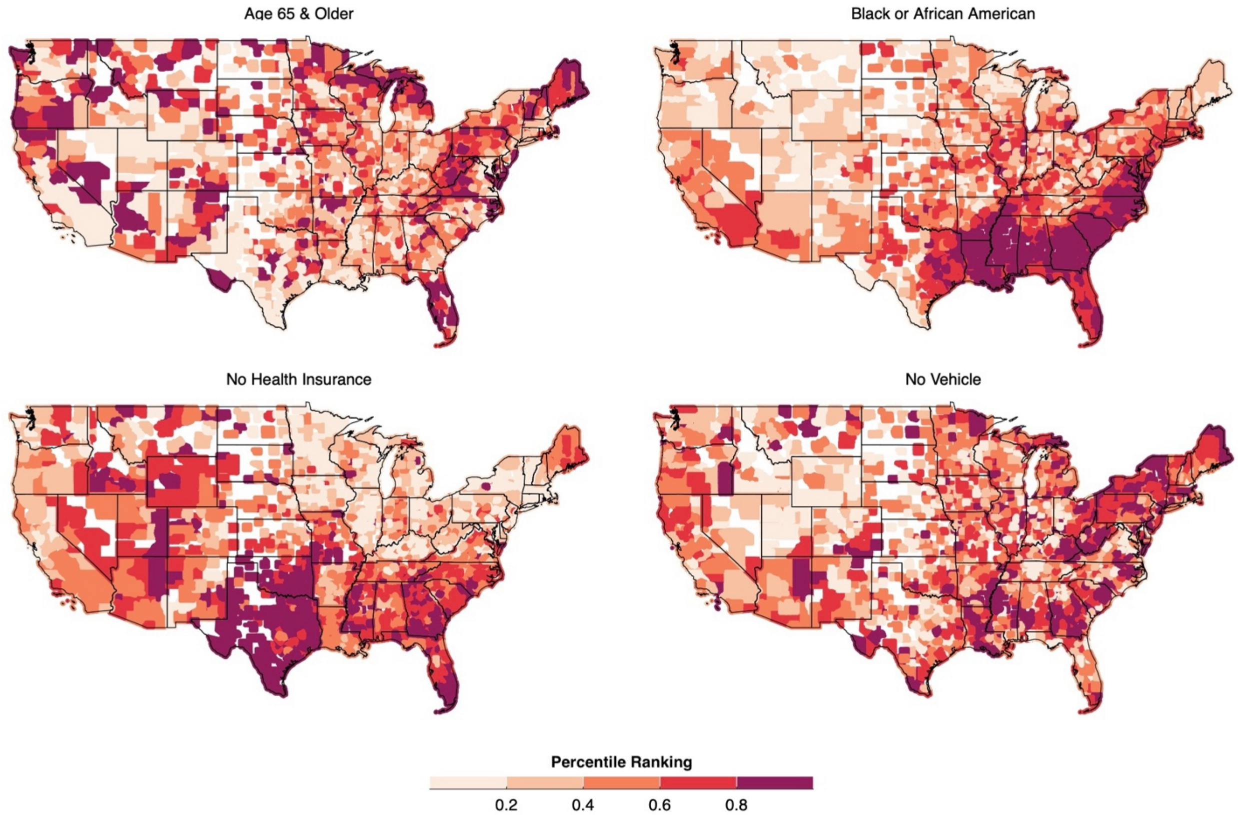
Prior studies have found that weather, such as temperature and precipitation, can affect households' consumption behaviors through seasonal demand, emotion, convenience, and product demand (Busse et al., 2015; He et al., 2022; Lee and Zheng, 2022). We obtain daily temperature and precipitation rasters from the PRISM Climate Group of Oregon State University, a standard source in the agricultural economics literature (see, for example, Schlenker and Roberts, 2009; Burke and Emerick, 2016). By converting the gridded data with a 4-km resolution to the county level, we thus calculate the weekly total precipitation and average temperature for each county.

### 2.4 County characteristics

Households with different socio-demographics may face different levels of adaptive capacity or present different preferences for mitigating suffering during natural disasters or conditions induced by environmental pollution (Rodriguez-Oreggia et al., 2013; Blaikie et al., 2014). To explore potential heterogeneity in responses to wildfire smoke exposure, we incorporate county-level data on the SVI developed by the CDC. The SVI offers socially and spatially relevant information that aids in enhancing community preparedness for emergency events and has been used in other studies (Flanagan et al., 2011; Lue and Wilson, 2017). In this study, we consider four SVIs, including the proportion of individuals with no health insurance in the total civilian noninstitutionalized population, the proportion of individuals aged 65 and older, the proportion of households with no vehicle access, and the proportion of Black/African American individuals. Figure 2 shows the spatial distribution of these four county characteristics in terms of percentile ranking.

[3] As a robustness check, we conduct the main analyses using the full sample in which we treat missing data as true zeros, a similar approach used by Beatty et al. (2019) when investigating the sales of emergency supplies before and after hurricanes. Table A1 in the appendix shows the regression results on the contemporaneous effects of wildfire smoke days on retail sales of six products using different sets of fixed effects.

**Figure 2. Spatial Distribution of County Characteristics**




### 2.5 Summary statistics

Table 1 presents summary statistics for the variables used in the analysis from 2006 to 2019, with a total of 1,853,129 observations at the county-by-week level. For wildfire smoke exposure (Panel A), the average number of smoke days is approximately 0.90 with a standard deviation of 1.55. As can be seen, some counties experienced wildfire smoke every day in a week. The mean concentration of smoke-driven PM2.5 is around 0.40 μg/m$^3$, with a standard deviation of 1.51 and a maximum reaching up to 179.5 μg/m$^3$. Regarding weekly retail sales (Panel B), air purifier sales average $182.4, while bottled water sales are considerably higher, averaging $24,297. Sales for cold remedies, cough drops, nasal products, and nutritional products vary, with means of $13,973, $1,008, $3,033, and $16,831, respectively. For county characteristics (Panel C), the average percentage of residents aged 65 and older is 18.73%, while 9.36% of the population does not have health insurance. Approximately 6.25% of households have no vehicle, and 9.67% of residents are

Black/African American. In terms of weather characteristics (Panel D), the average precipitation is 20.89 mm, while the mean temperature is approximately 12.98°C.

**Table 1: Summary Statistics**

| Variable | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|
| **Panel A: Wildfire smoke exposure** | | | | |
| Smoke days | 0.9024 | 1.5451 | 0 | 7 |
| Smoke-driven PM2.5 ($\mu g/m^3$) | 0.4001 | 1.5139 | 0 | 179.5 |
| **Panel B: Retail sales ($)** | | | | |
| Air purifier | 182.4 | 779.2 | 0 | 118,622 |
| Cold remedies | 13,973 | 47,110 | 0 | 2,356,212 |
| Cough drops | 1,008 | 3,798 | 0 | 230,011 |
| Nasal products | 3,033 | 10,339 | 0 | 452,819 |
| Nutritional products | 16,831 | 58,738 | 0 | 3,287,329 |
| Bottled water | 24,297 | 98,848 | 0 | 5,823,400 |
| **Panel C: County characteristics** | | | | |
| % Aged 65 and older | 18.73 | 4.457 | 3.000 | 57.80 |
| % No health insurance | 9.355 | 4.849 | 1.200 | 42.60 |
| % No vehicle | 6.253 | 3.670 | 0 | 77.60 |
| % Black/African American | 9.667 | 14.58 | 0 | 87.80 |
| **Panel D: Weather characteristics** | | | | |
| Precipitation (mm) | 20.89 | 25.90 | 0 | 1,036 |
| Mean temperature (°C) | 12.98 | 10.26 | -28.53 | 36.56 |

Note: Statistics summarize raw county-by-week data during 2006-2019. N=1,853,129.

## 3. Empirical Strategy

### 3.1 Wildfire smoke days and smoke-driven PM2.5

We first characterize the relationship between wildfire smoke days and smoke-driven PM2.5 at the county-week level using the following regression, which later serves as the first stage of our instrumental variable (IV) approach to estimate the impact of smoke-driven PM2.5 on retail sales:

$$PM2.5_{cwmy} = \beta_1 \times SmokeDay_{cwmy} + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m + \varepsilon_{cwmy} \qquad (1)$$

where $PM2.5_{cwmy}$ is the average smoke-driven PM2.5 level in the week $w$, month $m$, year $y$ for county $c$, $SmokeDay_{cwmy}$ is the number of days with wildfire smoke exposure in the week $w$, month $m$, year $y$ for county $c$, and $X_{cwmy}$ includes the total precipitation and average temperature in the week $w$, month $m$, year $y$ for county $c$. County-fixed effects $\alpha_c$ are included to control for any time-invariant county characteristics that could affect smoke-driven PM2.5. We also include year-fixed effects $\alpha_y$ and month-fixed effects $\alpha_m$ to control for seasonality in smoke-driven PM2.5. As robustness checks, we additionally include state-month and month-year fixed effects. Specifically, the state-year fixed effects control for annual trends in smoke-driven PM2.5, which may vary by state, and the month-year fixed effects control for monthly trends in smoke-driven PM2.5, which may vary by year. Standard errors are clustered at the county level. The coefficient of interest is $\beta_1$, which reflects the effect of an additional day of wildfire smoke in the exposed county on smoke-driven PM2.5.

### 3.2 Wildfire smoke days and retail sales

We begin our analysis of the effects of wildfire smoke exposure by analyzing the reduced-form relationship between days of wildfire smoke exposure and retail sales at the county-week level. Our main estimation equation is as follows:

$$Y_{cwmy} = \beta_2 \times SmokeDay_{cwmy} + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m + \varepsilon_{cwmy} \qquad (2)$$

where $Y_{cwmy}$ is the retail sales for the products of our interest (inverse hyperbolic sine transformed to address the issue of zero values) in the week $w$, month $m$, year $y$ for county $c$ and $SmokeDay_{cwmy}$ is the number of days with wildfire smoke exposure in the week $w$, month $m$, year $y$ for county $c$. Control variables and fixed effects remain the same as described in equation (1). Standard errors are clustered at the county level. The coefficient of interest is $\beta_2$, which reflects the effect of an additional day of wildfire smoke in the exposed county on retail sales.

### 3.3 Smoke-driven PM2.5 and retail sales

Prior studies find that smoke-driven PM2.5 can have significant effects on various outcomes such as health conditions (Reid et al., 2016), employment and labor force (Borgschulte et al., 2022), learning outcome (Wen and Burke, 2022), suicide deaths (Molitor et al., 2023), and outdoor recreational activities (Gellman et al., 2022). We further estimate the effects of smoke-driven PM2.5 on retail sales using the following equation:

$$Y_{cwmy} = \beta_3 \times PM2.5_{cwmy} + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m + \varepsilon_{cwmy} \quad (3)$$

where $Y_{cwmy}$ is the retail sales for the products of our interest (inverse hyperbolic sine transformed to address the issue of zero values) in the week $w$, month $m$, year $y$ for county $c$ and $PM2.5_{cwmy}$ is the average smoke-driven PM2.5 level in the week $w$, month $m$, year $y$ for county $c$. Control variables and fixed effects remain the same as described in equation (1). Standard errors are clustered at the county level. The coefficient of interest is $\beta_3$, which reflects the effect of the smoke-driven PM2.5 level in the exposed county on retail sales.

However, if the smoke-driven PM2.5 is endogenous or measured with errors,[4] the OLS approach using equation (3) will produce a biased estimate of $\beta_3$. To address this issue, we use an IV estimation strategy that leverages the quasi-random variation in the PM2.5 level generated by wildfire smoke, where our first-stage estimation equation is equation (1). Specifically, we implement a standard two-stage least squares (2SLS) estimation approach with one excluded instrument variable ($SmokeDay_{cwmy}$). The identifying assumption of our instrumental variables (IV) approach is that, after controlling for many fixed effects and weather factors, changes in a county's weekly wildfire smoke exposure are unrelated to changes in the county's retail sales except through their influence on air pollution. Our identification thus relies on the fact that a county's year-over-year variation in wildfire smoke exposure is driven largely by quasi-random factors, which are unlikely to be correlated with unobservable determinants of retail sales.

[4] Similarly, Borgschulte et al. (2022) use wildfire smoke days as an instrument for PM2.5 to estimate its impact on labor market outcomes and Molitor et al. (2023) use wildfire smoke days as an instrument for PM2.5 to estimate its impacts on suicide rates. More generally, other studies have used wind direction (Deryugina et al., 2019; Anderson, 2020), thermal inversion (Arceo et al. 2016; Sager, 2019; Deschenes et al. 2020; Liang et al. 2023), and atmospheric temperature inversions (Bondy et al., 2020) as an instrumental variable for assessing the effects of air pollution on a variety of outcomes.

### 3.4 Dynamic effects of wildfire smoke days

Previous specifications mainly consider the contemporaneous effects of wildfire smoke exposure on retail sales. However, it is reasonable that households' reactions to wildfire smoke may not occur immediately and can exhibit delayed responses. We, therefore, explore whether and how past wildfire smoke exposure influences current retail sales, which can help identify patterns in demand for adaptation and thus inform public health strategies to mitigate the impact of future wildfires. We thus estimate a distributed lag model as follows:

$$Y_{cwmy} = \sum_{t=0}^{t=4} \beta_{w-t} \times SmokeDay_{cmy,w-t} + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m + \varepsilon_{cwmy} \quad (4)$$

where $SmokeDay_{cmy,w-t}$ is the number of days with wildfire smoke exposure in a county-month-year-lagged week (of $w-t$). Particularly, the cumulative effect of $SmokeDay_{cmy,w-t}$ on retail sales is obtained by $\sum_{t=0}^{t=4} \beta_{w-t}$, which sums up the contemporaneous effect ($\beta_{w-0}$) and lagged effects ($\beta_{w-t}, t = 1, \ldots, 4$).

### 3.5 Nonlinear effects of wildfire smoke exposure

To examine the potential nonlinear effects of wildfire smoke exposure on retail sales and whether the mild and extreme smoke exposure may affect retail sales differently compared to the baseline scenario when there is no smoke exposure, we estimate the following equation:

$$Y_{cwmy} = \sum_{i=1}^{i=7} \beta^i \times SmokeDay_{cwmy}^i + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m + \varepsilon_{cwmy} \quad (5)$$

where $SmokeDay_{cwmy}^i$ are dummies indicating whether a county-week has 1, 2, 3, 4, 5, 6, or 7 days with wildfire smoke exposure, with no wildfire smoke exposure in a week as the baseline. The coefficients of interest are $\beta^i$ ($i = 1, \ldots, 7$), which quantify the effects of different numbers of smoke days on retail sales relative to the baseline scenario when there is no wildfire smoke exposure in a week.

### 3.6 Heterogeneity by county characteristics

To explore potential heterogeneity in responses to wildfire smoke exposure, we create dummies for whether a county is below the 20 percentile, between the 20 percentile and 40 percentile, between the 40 percentile and 60 percentile, between the 60 percentile and 80 percentile, and between the 80 percentile and 100 percentile with respect to four SVIs. For each SVI, we estimate heterogeneity using an augmented version of our main specification (equation 2) that fully interacts the percentile dummies with the number of smoke days, where the category "below the 20 percentile" is used as the baseline:

$$\begin{aligned} Y_{cwmy} = {} & \beta_4 \times SmokeDay_{cwmy} + \beta_5 \times SmokeDay_{cwmy} \times 1^{SVI}_{\in[20,40)} \\ & + \beta_6 \times SmokeDay_{cwmy} \times 1^{SVI}_{\in[40,60)} + \beta_7 \times SmokeDay_{cwmy} \times 1^{SVI}_{\in[60,80)} \\ & + \beta_8 \times SmokeDay_{cwmy} \times 1^{SVI}_{\in[80,100]} + \gamma \times X_{cwmy} + \alpha_c + \alpha_y + \alpha_m \\ & + \varepsilon_{cwmy} \end{aligned} \tag{6}$$

where $1^{SVI}_{\in[20,40)}$, $1^{SVI}_{\in[40,60)}$, $1^{SVI}_{\in[60,80)}$, and $1^{SVI}_{\in[80,100]}$ are dummies indicating the corresponding percentile range. The coefficients of interest are $\beta_5$, $\beta_6$, $\beta_7$, and $\beta_8$, which reflect the effects of smoke days per week on retail sales for counties with a higher percentile of SVI relative to the baseline (i.e., below the 20 percentile).

## 4. Results

### 4.1 Contemporaneous effects of wildfire smoke exposure

Table 2 shows the main results on the contemporaneous effects of wildfire smoke exposure. We establish several findings. First, there is a statistically significant and positive relationship between smoke exposure (measured as the number of smoke days per week) and smoke-driven PM2.5. Column (1) in Panel A of Table 2 shows that an increment of one day exposed to wildfire smoke during the week leads to an average increase of 0.59 μg/m$^3$ in smoke-driven PM2.5 on a weekly basis.

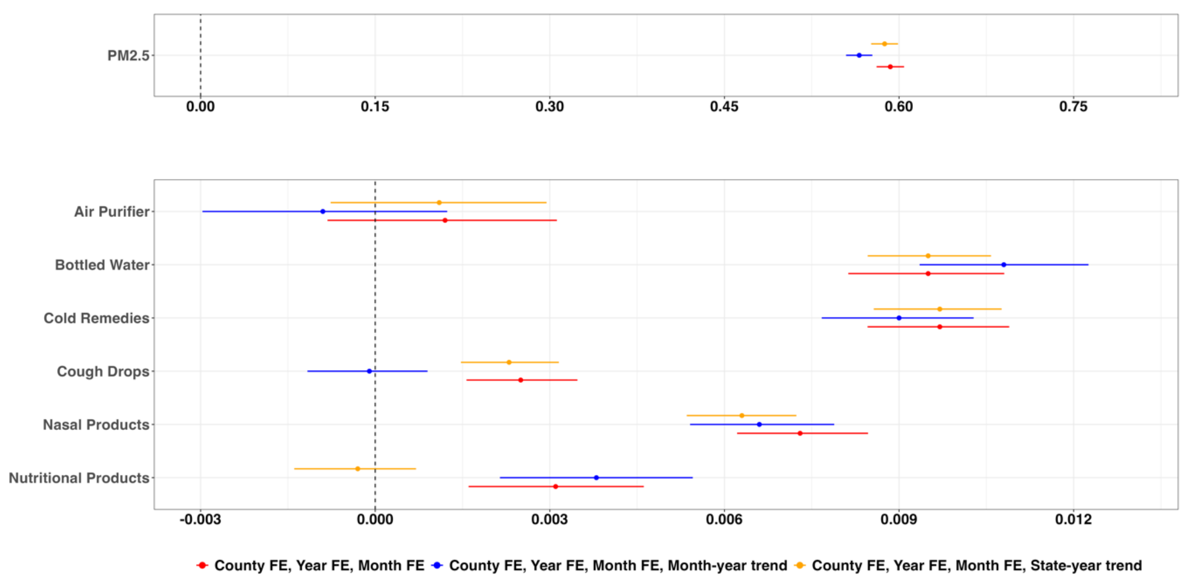
**Table 2: Contemporaneous Effects of Wildfire Smoke Exposure**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | PM2.5 | Air Purifier | Cold Remedies | Cough Drops | Nasal Products | Nutritional Products | Bottled Water |
| | | | **Panel A. First-stage and reduced-form estimates** | | | | |
| SmokeDay | 0.5925*** | 0.0012 | 0.0097*** | 0.0025*** | 0.0073*** | 0.0031*** | 0.0095*** |
| | (0.0060) | (0.0010) | (0.0006) | (0.0005) | (0.0006) | (0.0008) | (0.0007) |
| | | | **Panel B. OLS estimates** | | | | |
| PM2.5 | — | 0.0156*** | 0.0018*** | 0.0004 | 0.0038*** | 0.0012** | 0.0080*** |
| | — | (0.0015) | (0.0005) | (0.0004) | (0.0005) | (0.0006) | (0.0007) |
| | | | **Panel C. IV estimates** | | | | |
| PM2.5 | — | 0.0019 | 0.0163*** | 0.0043 | 0.0124*** | 0.0052*** | 0.0160*** |
| | — | (0.0017) | (0.0011) | (0.0008) | (0.0010) | (0.0013) | (0.0011) |
| Kleibergen-Paap F | — | 9,673 | 9,673 | 9,673 | 9,673 | 9,673 | 9,673 |
| Outcome mean | 0.4001 | 183 | 14,002 | 1,010 | 3,040 | 16,884 | 24,358 |
| Observations | 1,853,129 | 1,853,129 | 1,853,129 | 1,853,129 | 1,853,129 | 1,853,129 | 1,853,129 |

Note: An observation is a county-week. Panel A reports the contemporaneous effects of wildfire smoke days on PM2.5 (equation 1) and retail sales of six products (equation 2). Panels B and C report the impact of smoke-driven PM2.5 on retail sales of six products (equation 3), where PM2.5 is instrumented for using wildfire smoke days in Panel C. The outcome variables in columns (2)-(7) are inverse hyperbolic sine transformed. In all columns, the outcome mean is the mean of the dependent variable. All regressions include the average precipitation and temperature at the county-week level, county-fixed effects, month-fixed effects, and year-fixed effects. Standard errors, clustered at the county level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Second, columns (2)-(7) in Panel A of Table 2 present the effects of the number of smoke days in a week on the retail sales of our selected products. We find that an increase in smoke days per week leads to increased retail sales by 0.25%-0.97%, depending on the product. Notably, the top three products exhibiting the highest increases in retail sales are cold remedies, bottled water, and nasal products. These results make sense as the presence of harmful pollutants and irritants produced by wildfire smoke can worsen respiratory conditions such as colds and allergies (Reid et al., 2016; Xu et al., 2020). Moreover, prolonged exposure to wildfire smoke can lead to dehydration, discomfort, and water quality contamination (Stone et al., 2019; Proctor et al., 2020), prompting individuals to increase their consumption of bottled water (Xu et al., 2020). However, we do not find a statistically significant effect on the sales of air purifiers, which aligns with our expectations considering their durability and higher cost relative to other products.[5] As robustness checks, Figure 3 presents the coefficient estimates in Panel A of Table 2, together with corresponding regression results when additional fixed effects are added, as discussed in Section 3. Generally, we find that our results are quite robust across model specifications when different fixed effects are used.

**Figure 3: Contemporaneous Effects of Wildfire Smoke Days on PM2.5 and Retail Sales**




Note: This figure shows the coefficient estimates for the contemporaneous effects of wildfire smoke days on PM2.5 (equation 1) and retail sales of six products (equation 2), with the horizontal lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

[5] An examination of the sales of air purifier filters or facial masks could provide additional insights into how households respond to wildfire smoke exposure. Unfortunately, such data is not available in the NielsenIQ dataset.

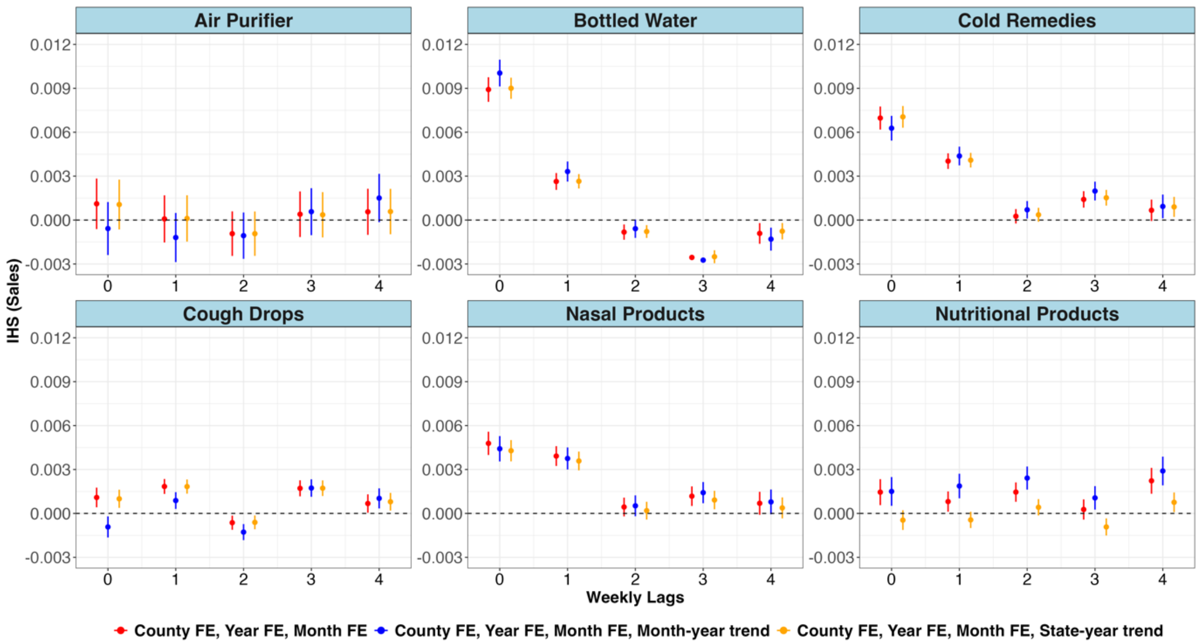
Third, Panel B of Table 2 shows the impacts of smoke-driven PM2.5 on retail sales of these products. We find that a one-unit increase in PM2.5 (1 $\mu g/m^3$) leads to an increase in retail sales by 0.12%-1.56%, depending on the product. Notably, air purifiers, bottled water, and cough drops exhibit the highest increases in sales. Prior studies find that smoke-driven PM2.5 can lead to a monotonically increasing scale of emergency department visits for acute respiratory conditions (Heft-Neal et al., 2023). Our study complements their findings by highlighting another common household mitigation behavior in response to wildfire smoke. In Panel C of Table 2, we report the IV estimates, which are generally larger than the OLS estimates in Panel B.

### 4.2 Dynamic effects of wildfire smoke days

While the contemporaneous effects of wildfire smoke exposure are compelling, these results do not account for the potential dynamic relationship between smoke exposure and consumption behaviors, an important measure for adaptation. As noted by Heft-Neal et al. (2023), household decisions to seek medical treatment may occur after weeks of exposure to wildfires. To explore this possibility, we adopt the approach used by Lee and Zheng (2022) and Heft-Neal et al. (2023) by adding up to four weeks of weekly lags in our model and estimating a distributed lag model using equation (4). Figure 4 shows the results.

First, consistent with our previous findings, we observe that an additional smoke day per week leads to significant increases in retail sales, except for air purifiers. Second, if we focus on the one-week lag of exposure, we can still see a statistically significant and positive effect on retail sales, although the effects are smaller compared to the week of exposure. This result indicates that increased household spending can occur in the subsequent week following wildfire smoke exposure. For the over-the-counter medical supplies, including cold remedies, cough drops, nasal products, and nutritional products, our findings indicate an increased sales trend persisting up to even four weeks following a wildfire occurrence. When we aggregate these coefficient estimates over the course of five weeks, we find statistically significant cumulative effects for most of these products (i.e., 1.33% for cold remedies, 1.10% for nasal products, 0.73% for bottled water, 0.62% for nutritional products, and 0.47% for cough drops). The lagged effects provide a more comprehensive understanding of the dynamics between wildfire smoke exposure and household adaptation. These results also highlight the prolonged influence of wildfire smoke exposure on household consumption behaviors, rather than solely attributing it to a delayed decision-making process, as pointed out by Lee and Zheng (2022) when examining how extreme temperatures affect household retail consumption.

**Figure 4: Dynamic Effects of Wildfire Smoke Days on Retail Sales**



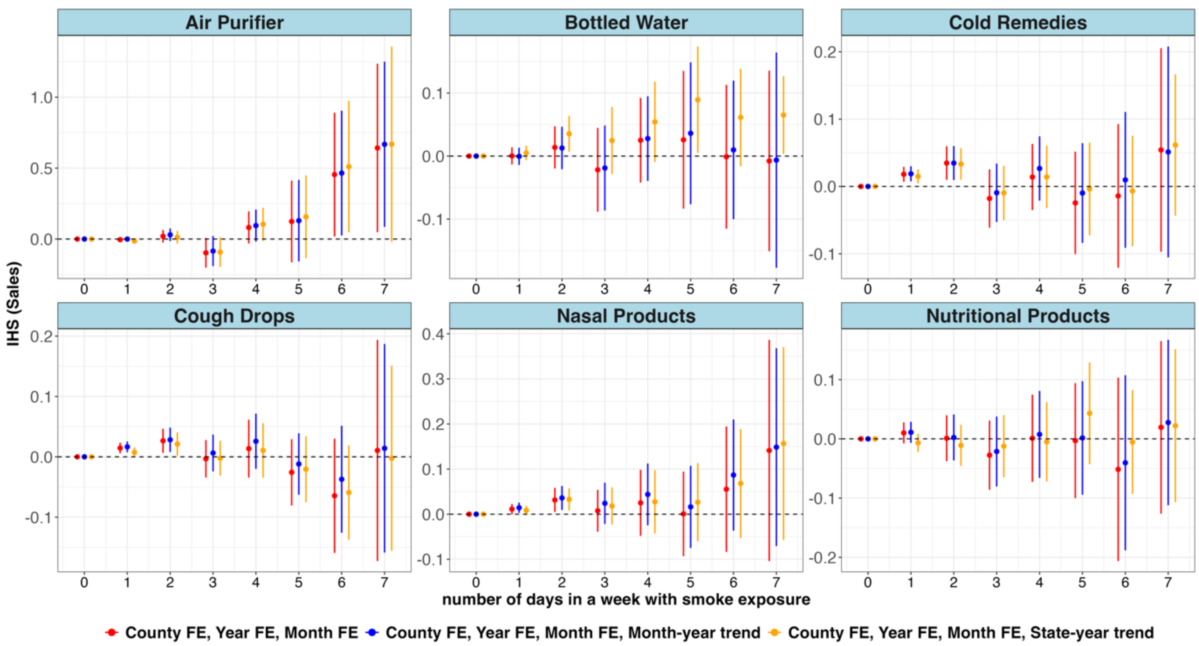

Note: This figure shows the coefficient estimates for the dynamic effects of wildfire smoke days on retail sales of six products (equation 4), with the verticle lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

### 4.3 Nonlinear effects of wildfire smoke exposure

Figure 5 reveals several intriguing patterns regarding the nonlinear effects of wildfire smoke exposure on retail sales, suggesting distinct consumer behaviors based on the severity of wildfire smoke exposure. First, we find that counties exposed to wildfire smoke for only 1 and 2 days per week have increased retail sales for cold remedies, cough drops, and nasal products, ranging from 0.74% to 3.6%. This suggests that individuals are more likely to purchase these items in response to mild wildfire smoke exposure, potentially to alleviate symptoms associated with respiratory conditions. Second, for counties exposed to 6 and 7 days of wildfire smoke per week, we observe substantial increases in retail sales of air purifiers by 45.5% and 66.9%, respectively. This indicates a strong demand for air purifiers during periods of prolonged and severe smoke exposure, as individuals seek means to improve indoor air quality and protect themselves from the health risks posed by wildfire smoke.

By recognizing the varying consumer responses to different levels of wildfire smoke exposure, public health officials can prioritize the allocation of resources and implement strategies to address the specific needs of communities at different stages of wildfire smoke exposure. Ensuring access to respiratory remedies during mild smoke exposure and facilitating the availability of air purifiers during severe smoke exposure are vital steps in safeguarding the health and well-being of affected populations.

**Figure 5: Nonlinear Effects of Wildfire Smoke Days**

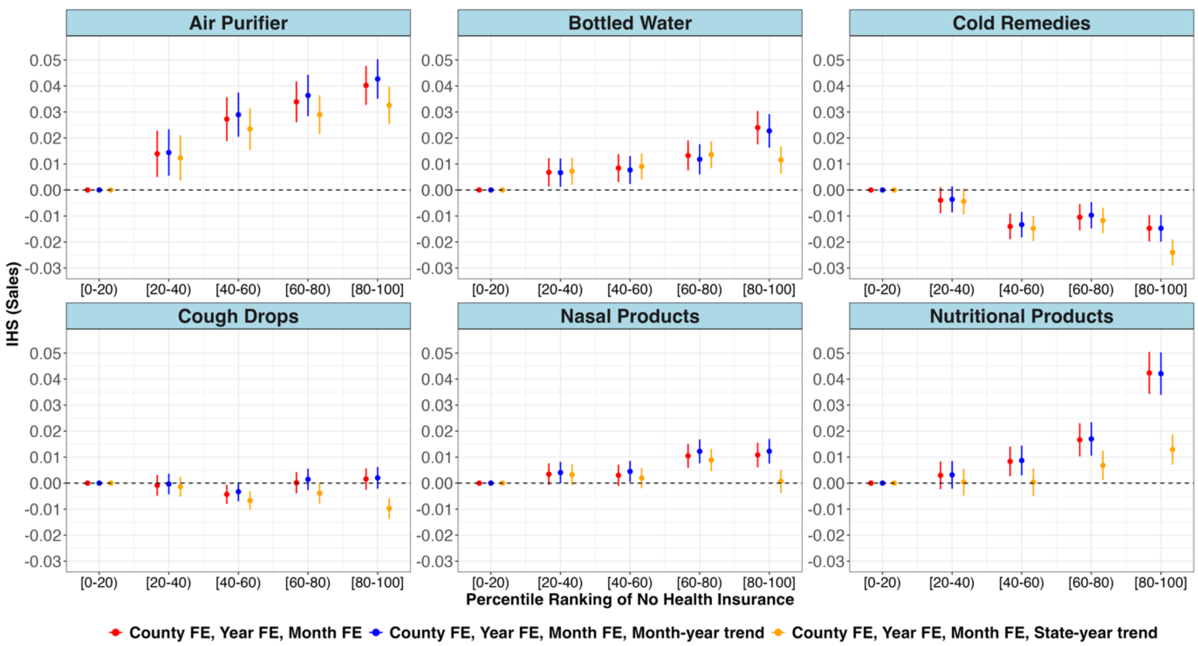



Note: This figure shows the coefficient estimates for the nonlinear effects of wildfire smoke days on retail sales of six products (equation 5), with the vertical lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

### 4.4 Heterogeneity by county characteristics

Figures 6-9 plot the results from the heterogeneity analysis using the four county-level SVIs. First, we find that counties with a higher proportion of individuals with no health insurance exhibit a tendency toward increased sales of most products in response to smoke exposure (Figure 6). As individuals may pursue health insurance as a proactive measure to protect themselves from the impacts of air pollution (Chen and Chen, 2020), this finding suggests that individuals without health insurance may be "forced" to rely on retail stores and purchase medical products as a means of mitigating the health risks associated with smoke exposure. This may impose extra financial burdens on those vulnerable populations. Public health interventions aimed at adequate access to affordable health insurance or alternative mitigation strategies could help address the needs of this vulnerable population.

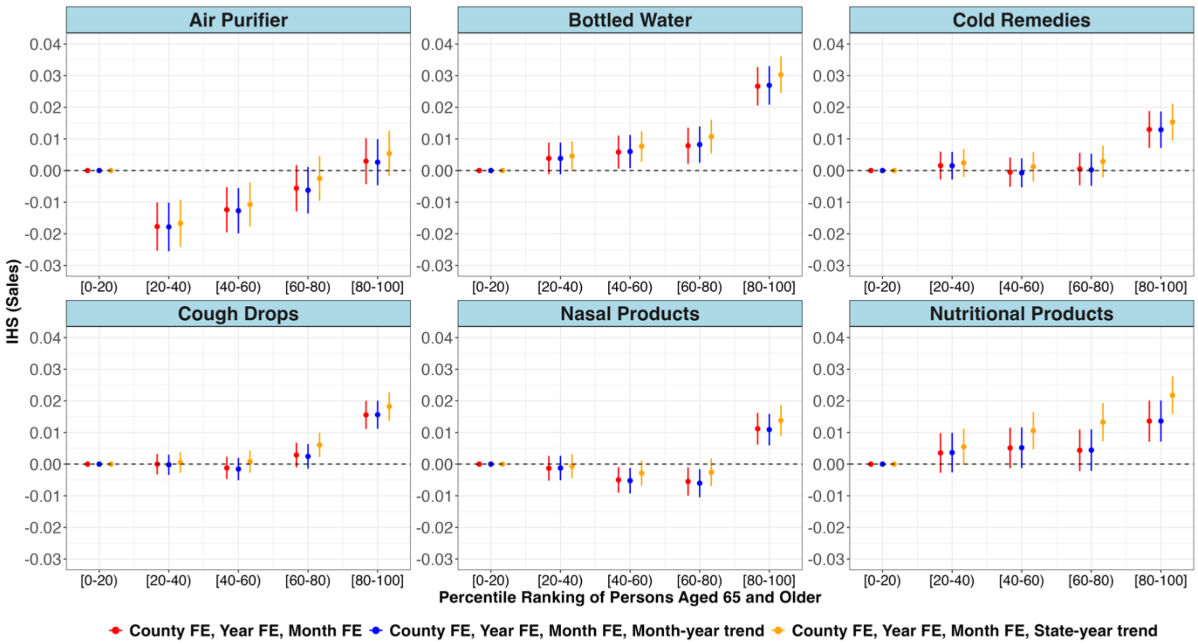
**Figure 6: Heterogeneous Effects of Wildfire Smoke Days: No Health Insurance**




Note: This figure shows the coefficient estimates for the heterogeneous effects of wildfire smoke days on retail sales of six products (equation 6) based on the percentile ranking of no health insurance, with the vertical lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

Second, counties with a higher share of individuals aged 65 and older also show elevated retail sales of most products, particularly those directly related to respiratory medicine (Figure 7). The result is consistent with the finding that individuals aged 65 years and older are especially susceptible to the detrimental impacts of wildfire smoke, placing them at a heightened risk for experiencing short-term respiratory issues (Arriagada et al., 2019). This finding underscores the heightened vulnerability of the elderly to the adverse effects of smoke exposure and the increased demand for respiratory health products. Tailored outreach efforts and preventive measures aimed at protecting the respiratory health of older adults could prove beneficial in mitigating the potential health risks posed by wildfire smoke.

**Figure 7: Heterogeneous Effects of Wildfire Smoke Days: Aged 65 and Older**

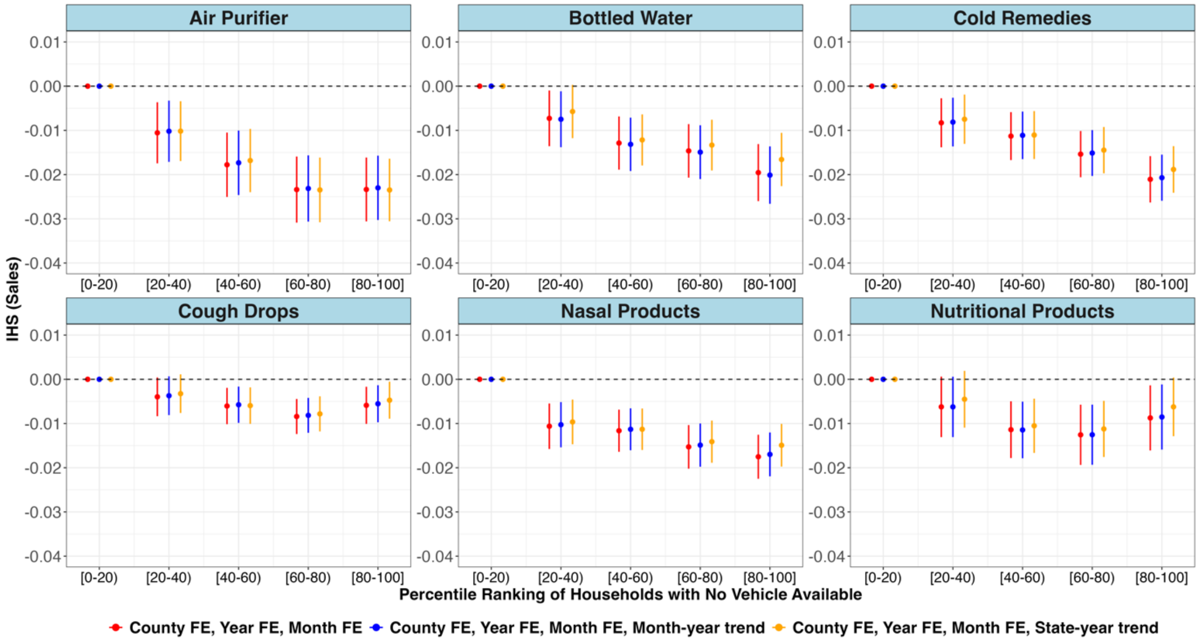



Note: This figure shows the coefficient estimates for the heterogeneous effects of wildfire smoke days on retail sales of six products (equation 6) based on the percentile ranking of persons aged 65 and older, with the vertical lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

Third, counties with a higher proportion of individuals without access to a vehicle tend to have lower retail sales of all products (Figure 8). This suggests that transportation limitations may impede individuals from accessing and purchasing necessary products in response to wildfire smoke exposure.[6] It highlights the importance of considering transportation barriers and exploring alternative distribution channels, such as community-based initiatives or mobile services, to ensure equitable access to essential items during periods of heightened smoke exposure.

[6] One may be concerned that households could purchase those products online instead of visiting stores. However, this is unlikely the case in our study. While we do not have online sales data to provide direct evidence, we find that the county-level percent of individuals without access to a vehicle is highly and positively correlated with the percent of households without a computer with a broadband internet subscription (a correlation coefficient of 0.69).

**Figure 8: Heterogeneous Effects of Wildfire Smoke Days: No Vehicle**

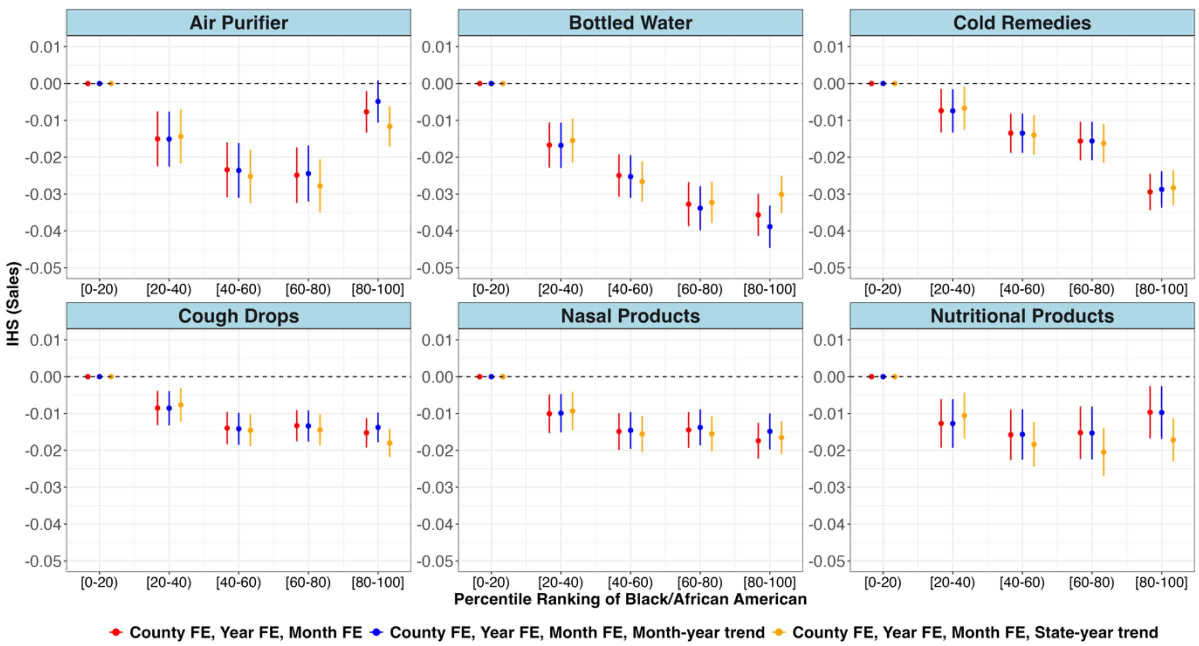



Note: This figure shows the coefficient estimates for the heterogeneous effects of wildfire smoke days on retail sales of six products (equation 6) based on the percentile ranking of no vehicle available, with the vertical lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

Lastly, we find counties with a higher proportion of Black/African American residents tend to display lower retail sales of all products (Figure 9). This result raises concerns about potential disparities in access to resources and information, which may hinder the ability of marginalized communities to respond effectively to wildfire smoke exposure. However, the root cause of this pattern, whether it is due to demand or supply constraints, remains an open question that merits further investigation. If it is predominantly a demand issue, the implementation of educational programs may be beneficial. On the other hand, if it is largely a supply problem, policy efforts should not only address supply chain efficiency but also work towards expanding the number of supply outlets in these communities. Regardless of the cause, it is imperative to address these disparities and strive for equitable access to resources and information, in an effort to reduce health inequalities linked to wildfire smoke exposure.

Taken together, these findings not only shed light on the varied household responses to smoke exposure but also emphasize the need for targeted interventions and tailored public health strategies to address the specific needs of different communities. Understanding the demographic and socioeconomic factors that influence consumer behavior can inform the development of more effective policies and interventions aimed at mitigating the health risks associated with smoke exposure and promoting health equity.

**Figure 9: Heterogeneous Effects of Wildfire Smoke Days: Black/African Americans**




Note: This figure shows the coefficient estimates for the heterogeneous effects of wildfire smoke days on retail sales of six products (equation 6) based on the percentile ranking of Black/African Americans, with the vertical lines denoting the 95% confidence intervals for the coefficient estimates. Three model specifications, each with a different set of fixed effects, are compared.

## 5. Discussion and conclusions

Wildfire events have become increasingly frequent and severe in recent decades across the United States. Our analysis reveals that increased wildfire smoke days per week lead to elevated retail sales of cold remedies, cough drops, nasal products, nutritional products, and bottled water. To shed more light on the significant impacts of wildfire smoke exposure, we conduct a back-of-the-envelope analysis based on our reduced-form results. Specifically, we quantify the aggregate additional household spending on the analyzed healthcare products attributable to wildfire smoke exposure by multiplying the average annual household spending on each product, the annual count of households within the United States, the impact of wildfire smoke exposure ($\beta_2$ in equation 2), and the mean frequency of days marked by wildfire smoke per week during the corresponding year.[7]

Table A2 and Figure A1 in the appendix illustrate an overall upward trend of additional household spending on healthcare products between 2006 and 2019 due to wildfire smoke exposure. Most products show synchronized peaks in spending increases due to wildfire smoke exposure, notably occurring in 2012 and 2018. This ascending trend largely mirrors the intensified levels of wildfire smoke exposure during the same period. In 2018, the annual household spending on these products exhibited the most significant changes. Specifically, there was an increase of $0.65 million in spending for air purifiers, $55.62 million for bottled water, $34.09 million for cold remedies, $0.68 million for cough drops, $6.46 million for nasal products, and $28.18 million for nutritional products. Aggregating these individual contributions culminates in a noteworthy annual sales increment of $125.68 million attributed to wildfire smoke exposure.

In the environmental justice literature, socioeconomically vulnerable places are found to be more polluted, and environmental policies may even exacerbate pollution in poor communities (Fullerton and Muehlegger, 2019; Holland et al., 2019; Hernández-Cortés, 2022; Currie et al., 2023; Hernández-Cortés and Meng, 2023). These cases beg the question of how government policies should be designed and implemented to address environmental justice. Although exposure to ambient PM2.5 from wildfire smoke appears to be similar across racial subgroups and varying degrees of economic disadvantage (Burke et al., 2021; Burke et al., 2022; Wen and Burke 2022), the unequal protection by government agencies underscores the significance of personal proactive measures. Our heterogeneity analysis reveals the unequal demand for adaptation to wildfire smoke exposure among disadvantaged communities and underscores the necessity for targeted policies designed to address inequality. As societal intervention is essential for mitigating the adverse health consequences of wildfire exposure (Xu et al., 2020), these findings emphasize the critical role of societal action in reducing such risks.

[7] To calculate the total increase in dollar values attributable to annual wildfire smoke exposure, we use the average annual household spending on each product as the benchmark instead of county-level retail sales for the following reasons. First, while retail stores included in the NielsenIQ Retailer Scanner Data are representative in each county, not all retail stores are included and we lack information on the sampling method of participating retail stores in each county. Thus, we are not able to aggregate the total retail sales in each county. Second, annual household spending is a reliable alternative to retail sales, given that the NielsenIQ Consumer Panel Data has a representative sample of households in the United States. Since we have information on the total number of households in the country, we can calculate aggregate household expenditures based on the average annual household spending.

The increase in healthcare products purchased by seniors due to wildfire smoke exposure suggests that there is a need to fortify public health and healthcare policies to adequately cater to seniors' health requirements in the face of increasing wildfire smoke exposure. Furthermore, the rise in purchases of OTC healthcare items by uninsured individuals, prompted by wildfire smoke exposure, emphasizes the need for extending health insurance coverage to mitigate healthcare accessibility disparities. It also underscores the importance of initiating subsidy programs to assist uninsured individuals grappling with elevated healthcare costs due to smoke exposure. Our study places particular emphasis on OTC medicines, which empower households to engage in self-treatment promptly and effectively. Given that each dollar spent on OTC medicines can yield over $7 in savings for the U.S. healthcare system through the reduction in physician visits and spending on more expensive medical interventions,[8] ensuring a robust supply of OTC medicines during instances of wildfire smoke exposure can yield substantial conservation of healthcare resources.

At the same time, the observed trend of individuals lacking vehicle access purchasing fewer healthcare products and bottled water in response to wildfire smoke exposure calls for the enhancement of public transportation and possible delivery services, especially in wildfire-prone regions, to enable all citizens to procure necessary supplies during wildfire events. Additionally, it highlights the significance of ensuring the local availability of these critical items as a means of household adaptation. To address the needs of households without vehicle access, policymakers could incentivize the establishment of businesses in underserved regions or implement mobile distribution services in times of emergencies, thereby fostering equitable access to essential resources.

In conclusion, our study underscores the multifaceted impacts of wildfire smoke exposure on retail sales and healthcare adaptation. Increased wildfire smoke exposure has been found to catalyze elevated retail sales of healthcare products. Additionally, nonlinear responses to exposure intensity, characterized by a rise in respiratory remedy sales during mild exposure and air purifier demand during severe exposure, highlight the importance of tiered response strategies and financial support policies. Finally, varying demand patterns among seniors, uninsured individuals, people without vehicle access, and Black/African American communities underline the necessity

[8] This statistic is based on data from the Consumer Healthcare Products Association's report on the "Value of OTC Medicines to the U.S. Healthcare System." See here for more details: https://www.iriworldwide.com/IRI/media/Library/Publications/CHPA_IRI_OTC-Value_WhitePaper.pdf

of policy interventions that consider the unique needs of these socioeconomically vulnerable groups. This study reinforces the critical need for comprehensive, targeted, and dynamic policy strategies that can promote equitable health outcomes and community resilience in the face of increasing wildfire incidents.

**References:**

Anderson, M. L. (2020). As the wind blows: The effects of long-term exposure to air pollution on mortality. *Journal of the European Economic Association*, 18(4), 1886-1927.

Anderson, S. E., Plantinga, A. J., & Wibbenmeyer, M. (2023). Unequal treatments: Federal wildfire fuels projects and socioeconomic status of nearby communities. *Environmental and Energy Policy and the Economy*, 4(1), 177-201.

Arceo, E., Hanna, R., & Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *The Economic Journal*, 126(591), 257-280.

Arriagada, N. B., Horsley, J. A., Palmer, A. J., Morgan, G. G., Tham, R., & Johnston, F. H. (2019). Association between fire smoke fine particulate matter and asthma-related outcomes: Systematic review and meta-analysis. *Environmental Research*, 179, 108777.

Banzhaf, S., Ma, L., & Timmins, C. (2019). Environmental justice: The economics of race, place, and pollution. *Journal of Economic Perspectives*, 33(1), 185-208.

Beatty, T. K., Shimshack, J. P., & Volpe, R. J. (2019). Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes. *Journal of the Association of Environmental and Resource Economists*, 6(4), 633-668

Blaikie, P., Cannon, T., Davis, I., & Wisner, B. (2014). *At risk: Natural hazards, people's vulnerability and disasters*. Routledge.

Bondy, M., Roth, S., & Sager, L. (2020). Crime is in the air: The contemporaneous relationship between air pollution and crime. *Journal of the Association of Environmental and Resource Economists*, 7(3), 555-585.

Borgschulte, M., Molitor, D., & Zou, E. Y. (2022). Air pollution and the labor market: Evidence from wildfire smoke. *Review of Economics and Statistics*, 1-46.

Bresnahan, B. W., Dickie, M., & Gerking, S. (1997). Averting behavior and urban air pollution. *Land Economics*, 340-357.

Brey, S. J., & Fischer, E. V. (2016). Smoke in the city: How often and where does smoke impact summertime ozone in the United States? *Environmental science & technology*, 50(3), 1288-1294.

Burke, M., Driscoll, A., Heft-Neal, S., Xue, J., Burney, J., & Wara, M. (2021). The changing risk and burden of wildfire in the United States. *Proceedings of the National Academy of Sciences*, 118(2), e2011048118.

Burke, M., Emerick, K., 2016. Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy* 8: 106–140.

Burke, M., Heft-Neal, S., Li, J., Driscoll, A., Baylis, P., Stigler, M., … & Gould, C. F. (2022). Exposures and behavioural responses to wildfire smoke. *Nature Human Behaviour*, 6(10), 1351-1361.

Burkhardt, J., Bayham, J., Wilson, A., Carter, E., Berman, J. D., O'Dell, K., ... & Pierce, J. R. (2019). The effect of pollution on crime: Evidence from data on particulate matter and ozone. *Journal of Environmental Economics and Management*, 98, 102267.

Busse, M.R., Pope, D.G., Pope, J.C., & Silva-Risso, J., 2015. The psychological effect of weather on car purchases. *Quarterly Journal of Economics* 130: 371–414.

Centers for Disease Control and Prevention. (2020). CDC's social vulnerability index (SVI). *Agency for Toxic Substances and Disease Registry*.

Chakraborti, L., & Shimshack, J. P. (2022). Environmental disparities in urban Mexico: Evidence from toxic water pollution. *Resource and Energy Economics*, 67, 101281.

Chen, F., & Chen, Z. (2020). Air pollution and avoidance behavior: A perspective from the demand for medical insurance. *Journal of Cleaner Production*, 259, 120970.

Childs, M. L., Li, J., Wen, J., Heft-Neal, S., Driscoll, A., Wang, S., ... & Burke, M. (2022). Daily local-level estimates of ambient wildfire smoke PM2.5 for the contiguous US. *Environmental Science & Technology*, 56(19), 13607-13621.

Currie, J., Voorheis, J., & Walker, R. (2023). What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality. *American Economic Review*, 113(1), 71-97.

Delfino, R. J., Brummel, S., Wu, J., Stern, H., Ostro, B., Lipsett, M., ... & Gillen, D. L. (2009). The relationship of respiratory and cardiovascular hospital admissions to the southern California wildfires of 2003. *Occupational and environmental medicine*, 66(3), 189-197.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12), 4178-4219.

Deschenes, O., Greenstone, M., & Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the NOx budget program. *American Economic Review*, 107(10), 2958-2989.

Deschenes, O., Wang, H., Wang, S., & Zhang, P. (2020). The effect of air pollution on body weight and obesity: Evidence from China. *Journal of Development Economics*, 145, 102461.

Dulam, R., Furuta, K., & Kanno, T. (2021). Quantitative decision-making model to analyze the post-disaster consumer behavior. *International Journal of Disaster Risk Reduction*, 61, 102329.

Flanagan, B. E., Gregory, E. W., Hallisey, E. J., Heitgerd, J. L., & Lewis, B. (2011). A social vulnerability index for disaster management. *Journal of Homeland Security and Emergency management*, 8(1), 0000102202154773551792.

Floyd, T., & Ishdorj, A. (2022). Consumer purchasing behavior before, during and after a natural disaster: The Case of Hurricane Harvey. Working Paper.

Fullerton, D., & Muehlegger, E. (2019). Who bears the economic burdens of environmental regulations? *Review of Environmental Economics and Policy*.

Gellman, J., Walls, M., & Wibbenmeyer, M. (2022). Wildfire, smoke, and outdoor recreation in the Western United States. *Forest Policy and Economics*, 134, 102619.

Giaccherini, M., Kopinska, J., & Palma, A. (2021). When particulate matter strikes cities: Social disparities and health costs of air pollution. *Journal of Health Economics*, 78, 102478.

He, P., Liu, P., Qiu, Y., Liu, L., 2022. The weather affects air conditioner purchases to fill the energy efficiency gap. *Nature Communications* 13: 5772.

Heft-Neal, S., Gould, C. F., Childs, M. L., Kiang, M. V., Nadeau, K. C., Duggan, M., ... & Burke, M. (2023). Emergency department visits respond nonlinearly to wildfire smoke. *Proceedings of the National Academy of Science*s, 120(39), e2302409120.

Hernández-Cortés, D. (2022). The Distributional Consequences of Incomplete Regulation. Working Paper.

Hernández-Cortés, D., & Meng, K. C. (2023). Do environmental markets cause environmental injustice? Evidence from California's carbon market. *Journal of Public Economics*, 217, 104786.

Holland, S. P., Mansur, E. T., Muller, N. Z., & Yates, A. J. (2019). Distributional effects of air pollution from electric vehicle adoption. *Journal of the Association of Environmental and Resource Economists,* 6(S1), S65-S94.

Holstius, D. M., Reid, C. E., Jesdale, B. M., & Morello-Frosch, R. (2012). Birth weight following pregnancy during the 2003 Southern California wildfires. *Environmental health perspectives*, 120(9), 1340-1345.

Ito, K., & Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in China. *Journal of Political Economy*, 128(5), 1627-1672.

Janke, K. (2014). Air pollution, avoidance behaviour and children's respiratory health: Evidence from England. *Journal of health economics*, 38, 23-42.

Kar, S. K., Agrawal, A., & Singh, N. (2022). Disaster and consumption behavior. *In Panic buying and environmental disasters: Management and mitigation approaches* (pp. 97-113). Cham: Springer International Publishing.

Larson, L. R., & Shin, H. (2018). Fear during natural disaster: Its impact on perceptions of shopping convenience and shopping behavior. *Services Marketing Quarterly*, 39(4), 293-309.

Lee, S., & Zheng, S. (2022). Extreme temperature, adaptation capacity, and household retail consumption. *MIT Center for Real Estate Research Paper*, (22/10).

Liang, Y., Wang, D., Yang, H., Yuan, Q., & Yang, L. (2023). Examining the causal effects of air pollution on dockless bike-sharing usage using instrumental variables. *Transportation Research Part D: Transport and Environment*, 121, 103808.

Liao, L., Du, M., & Chen, Z. (2021). Air pollution, health care use and medical costs: Evidence from China. *Energy Economics*, 95, 105132.

Lue, E., & Wilson, J. P. (2017). Mapping fires and American Red Cross aid using demographic indicators of vulnerability. *Disasters*, 41(2), 409-426.

Miller, N., Molitor, D., & Zou, E. (2021). A causal concentration-response function for air pollution: evidence from wildfire smoke. *Work. Pap., Coll. Bus., Univ. Ill., Urbana-Champaign*.

Mohai, P., Pellow, D., & Roberts, J. T. (2009). Environmental justice. *Annual review of environment and resources*, 34, 405-430.

Molitor, D., Mullins, J. T., & White, C. (2023). Air pollution and suicide in rural and urban America: Evidence from wildfire smoke. *Proceedings of the National Academy of Sciences*, 120(38), e2221621120.

National Interagency Fire Center. (2022). Historical wildland fire information: Federal firefighting costs: Suppression only (1985–2020). https://www.nifc.gov/fire-information/statistics/suppression-costs

NOAA, National Centers for Environmental Information. (2023). U.S. Billion-Dollar Weather and Climate Disasters. https://www.ncei.noaa.gov/access/billions/. DOI: 10.25921/stkw-7w73

Plantinga, A. J., Walsh, R., & Wibbenmeyer, M. (2022). Priorities and effectiveness in wildfire management: evidence from fire spread in the western United States. *Journal of the Association of Environmental and Resource Economists*, 9(4), 603-639.

Proctor, C. R., Lee, J., Yu, D., Shah, A. D., & Whelton, A. J. (2020). Wildfire caused widespread drinking water distribution network contamination. *AWWA Water Science*, 2(4), e1183.

Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balmes, J. R., & Elliott, C. T. (2016). Critical review of health impacts of wildfire smoke exposure. *Environmental Health Perspectives*, 124(9), 1334-1343.

Rodriguez-Oreggia, E., De La Fuente, A., De La Torre, R., & Moreno, H. A. (2013). Natural disasters, human development and poverty at the municipal level in Mexico. *The Journal of Development Studies*, 49(3), 442-455.

Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management*, 98, 102250.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37), 15594-15598.

Sneath, J. Z., Lacey, R., & Kennett-Hensel, P. A. (2009). Coping with a natural disaster: Losses, emotions, and impulsive and compulsive buying. *Marketing letters*, 20, 45-60.

Stone, S. L., Anderko, L., Berger, M. F., Butler, C. R., Cascio, W. E., Clune, A., ... & Haskell, W. (2019). Wildfire smoke: A guide for public health officials. *US Environmental Protection Agency*.

Urbanski, S. P., Hao, W. M., & Baker, S. (2008). Chemical composition of wildland fire emissions. *Developments in environmental science*, 8, 79-107.

Wen, J., & Burke, M. (2022). Lower test scores from wildfire smoke exposure. *Nature Sustainability*, 5(11), 947-955.

Xu, R., Yu, P., Abramson, M. J., Johnston, F. H., Samet, J. M., Bell, M. L., ... & Guo, Y. (2020). Wildfires, global climate change, and human health. *New England Journal of Medicine*, 383(22), 2173-2181.

Zhang, J., & Mu, Q. (2018). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management*, 92, 517-536.

Zivin, J. G., & Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2), 119-128.

## Appendices for "A Burning Issue: Wildfire Smoke Exposure, Retail Sales, and Demand for Adaptation in Healthcare"

### Table A1: Contemporaneous Effects of Wildfire Smoke Days on Retail Sales

| | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|
| | Air Purifier | Cold Remedies | Cough Drops | Nasal Products | Nutritional Products | Bottled Water |
| | **Panel A. County FE, Year FE, and Month FE** | | | | | |
| SmokeDay | 0.0013 | 0.0086*** | 0.0027*** | 0.0067*** | 0.0023*** | 0.0081*** |
| | (0.0009) | (0.0009) | (0.0007) | (0.0007) | (0.0010) | (0.0010) |
| | **Panel B. County FE, Year FE, Month FE, and Month-year Trend** | | | | | |
| SmokeDay | -0.0005 | 0.0081*** | 0.0005 | 0.0061*** | 0.0028** | 0.0092*** |
| | (0.0010) | (0.0010) | (0.0008) | (0.0008) | (0.0011) | (0.0011) |
| | **Panel C. County FE, Year FE, Month FE, and State-year Trend** | | | | | |
| SmokeDay | 0.0010 | 0.0085*** | 0.0024*** | 0.0056*** | -0.0009 | 0.0076*** |
| | (0.0009) | (0.0007) | (0.0006) | (0.0006) | (0.0006) | (0.0007) |
| Outcome mean | 168 | 12,876 | 929 | 2,795 | 15,526 | 22,399 |
| Observations | 2,014,070 | 2,014,070 | 2,014,070 | 2,014,070 | 2,014,070 | 2,014,070 |

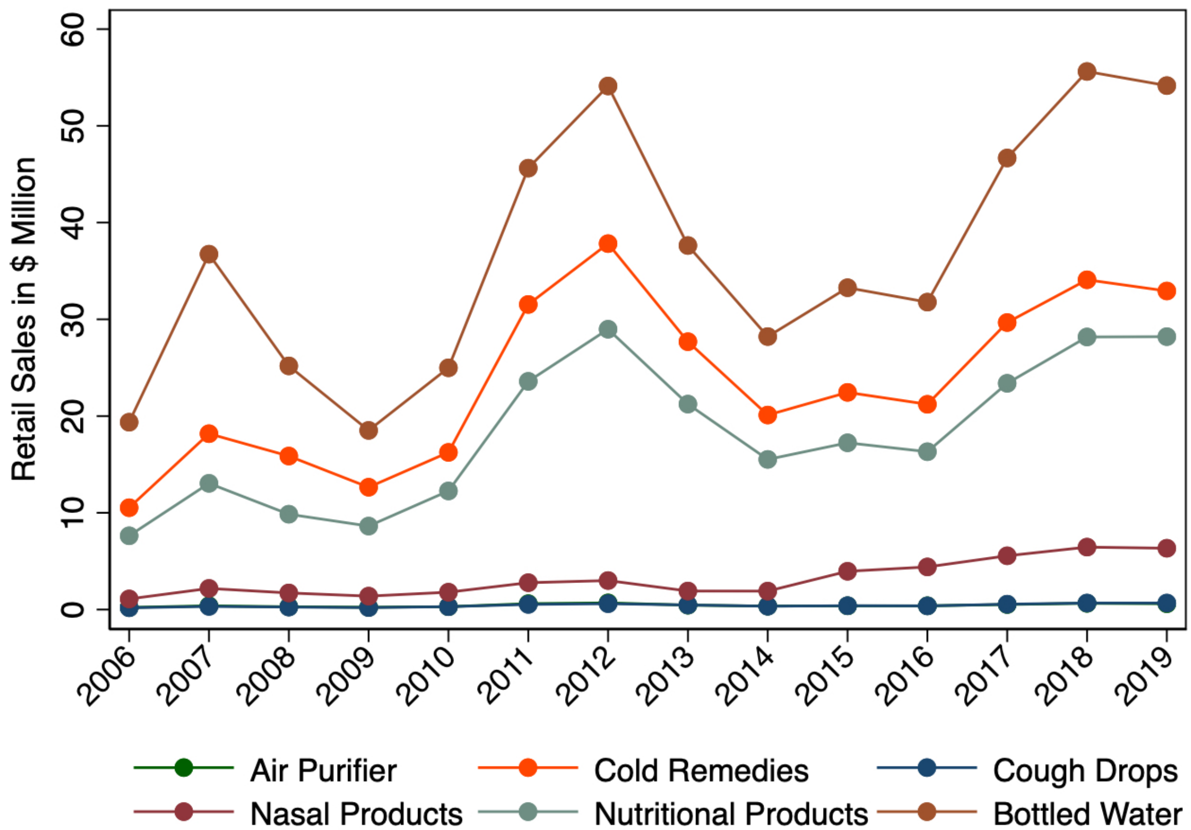
Note: This table reports the results from using the full sample that includes counties with no sales in a year. An observation is a county-week. All panels report the contemporaneous effects of wildfire smoke days on retail sales of six products (equation 2), where all outcome variables are inverse hyperbolic sine transformed. In all columns, the outcome mean is the mean of the dependent variable. All regressions include the total precipitation and average temperature at the county-week level, county-fixed effects, month-fixed effects, and year-fixed effects. Panel B additionally includes the month-year trend and Panel C additionally includes the state-year trend. Standard errors, clustered at the county level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table A2: Total Additional Household Spending on Selected Products Due to Wildfire Smoke Exposure

| Year | Air Purifier | Cold Remedies | Cough Drops | Nasal Products | Nutritional Products | Bottled Water |
|---|---|---|---|---|---|---|
| 2006 | 0.22 | 10.53 | 0.19 | 1.10 | 7.63 | 19.37 |
| 2007 | 0.39 | 18.18 | 0.33 | 2.19 | 13.05 | 36.74 |
| 2008 | 0.29 | 15.87 | 0.26 | 1.72 | 9.86 | 25.19 |
| 2009 | 0.24 | 12.65 | 0.21 | 1.39 | 8.63 | 18.52 |
| 2010 | 0.30 | 16.25 | 0.30 | 1.80 | 12.26 | 24.99 |
| 2011 | 0.61 | 31.54 | 0.54 | 2.78 | 23.59 | 45.63 |
| 2012 | 0.69 | 37.83 | 0.61 | 3.00 | 28.98 | 54.12 |
| 2013 | 0.46 | 27.69 | 0.48 | 1.92 | 21.24 | 37.63 |
| 2014 | 0.36 | 20.11 | 0.35 | 1.91 | 15.52 | 28.22 |
| 2015 | 0.39 | 22.45 | 0.40 | 3.96 | 17.24 | 33.27 |
| 2016 | 0.39 | 21.22 | 0.38 | 4.41 | 16.32 | 31.78 |
| 2017 | 0.53 | 29.67 | 0.56 | 5.56 | 23.39 | 46.68 |
| 2018 | 0.65 | 34.09 | 0.68 | 6.46 | 28.18 | 55.62 |
| 2019 | 0.61 | 32.93 | 0.68 | 6.34 | 28.21 | 54.16 |

Note: This table reports the total additional household spending on each product (in $ million) due to wildfire smoke exposure each year. The total additional household spending on each product is calculated by multiplying the average annual household spending on each product, the annual count of households within the United States, the impact of wildfire smoke exposure ($\beta_2$ in equation 2), and the mean frequency of days marked by wildfire smoke per week during the corresponding year.

## Figure A1: Total Additional Household Spending on Selected Products Due to Wildfire Smoke Exposure




Note: This figure plots the total additional household spending on each product (in $ million) due to wildfire smoke exposure each year. The total additional household spending on each product is calculated by multiplying the average annual household spending on each product, the annual count of households within the United States, the impact of wildfire smoke exposure ($\beta_2$ in equation 2), and the mean frequency of days marked by wildfire smoke per week during the corresponding year.