Sheltering from Wildfire Smoke: Evidence from Smart Thermostat Data

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Abstract

The response of individuals to wildfire smoke, particularly in terms of avoidance behaviors, has important implications for public health and policy. Using data from smart thermostat motion sensors, we examine two key avoidance strategies: spending more time indoors at home and traveling away from the affected area. Our analysis reveals that exposure to particulate matter from wildfire smoke significantly increases both behaviors. Moreover, we find substantial heterogeneity in responses by users who live in localities with different demographics and have different home values. In particular, those with more favorable socio-economic conditions consistently have a greater propensity to travel away from home due to wildfire driven PM2.5, indicating uneven capacity to undertake costly avoidance actions.

1 Introduction

Wildfire smoke and its components, particularly, fine particulate matter is known to have widespread and large health impacts. One important way that individuals attempt to protect themselves from degraded air quality during periods of wildfire smoke is by increasing the time they spend indoors (often at home). However, staying indoors is only a partial defense against exposure to wildfire smoke, and the degree to which it is successful at reducing exposure depends on characteristics of the home (O'Dell et al., 2022; Krebs and Neidell, 2024). Therefore, in periods of extreme wildfire smoke, some individuals may choose an especially costly form of avoidance: temporarily leaving the affected area altogether.

We examine (1) whether households in California increase their time spent at home and (2) whether they are more likely to temporarily vacate their residences during periods of high pollution from wildfire smoke. Our analysis employs a unique high-frequency dataset of smart thermostat readings, which has motion sensor(s) to detect the presence of the user(s) at home in 5-minute intervals. These data allow us to track individual users' time use behavior across normal times and smoke days and offer rich insights into their decision-making along the two margins of avoidance behavior.

The sample spans 2017-19, which includes two of the most destructive wildfire seasons in California history with massive losses and widespread smoke exposure. We link the thermostat data to pollution exposure as measured by air pollution monitor readings and smoke plume extents. For the analysis, we estimate a fixed effects model of the effect of a smoke-affected day on user behaviors. Our model accounts for each user's distinct time-use pattern across day-of-week, the seasonality and trends in wildfire smoke, and growth of the user base over time.

We find that individuals engage in both types of avoidance behaviors: (1) increasing time spent indoors and (2) temporarily vacating their residences to avoid high pollution. A day with smoke plume and high PM2.5 levels (*i.e.* $\geq 35\ \mu g/m^3$) leads to a 3.98 percent increase in time spent at home during daytime on weekdays, relative to the mean time spent at home. The response is weaker during evening hours, likely because there is less room for adjustment to begin with. One additional day with smoke plume and high PM2.5 in the previous seven days increases the probability of vacating residence by 11.4 percent of the mean probability of vacating residence. Finally,individuals avoid more hours of exposure by increasing time spent indoors compared to temporarily vacating their residences in one calendar year.

Our results indicate substantial heterogeneity in these behaviors based on aggregate demographics and individual home values. The response in time spent at home is stronger among users living in lower-income and less educated Census places, while the reverse is true for traveling away from home. Given that the latter is a much costlier but more effective margin of adjustment, these findings are indicative of unequal capacity of different demographic groups to undertake avoidance behavior. Additionally, stronger responses along the vacate home margin is observed among users living in higher-value homes relative to the median. Such disparities in avoidance behavior could lead to uneven exposure to wildfire smoke, making marginalized populations more vulnerable.

These findings add to the literature on costly avoidance behaviors regarding environmental risks. For example, Zivin and Neidell (2009) show that air quality alerts result in changes in decreased outdoor activity; Moretti and Neidell (2011) find evidence that avoidance of poor air quality results in decreased health impacts. Zivin et al. (2011) find that bottle water sales increase in places with Safe Water Drinking Act violations. More specifically, past studies find responses to wildfire smoke include increased defensive expenditures (e.g. home air purifiers, Richardson et al., 2012), labor force exits and changes in hours worked (Borgschulte et al., 2022), and declines in otherwise welfare-enhancing activities, such as recreation (e.g Gellman et al., 2023). Existing estimates indicate that costs of such behavior may be large. Borgschulte et al. (2022) estimate the annual costs of labor supply reductions due to smoke at approximately $94 billion in 2018 dollars. For those planning to visit a federal campground, Gellman et al. (2023) value welfare losses of wildfire smoke in the week of their visit at over $100 per trip. Our findings on both margins of adjustment are consistent with these studies. Traveling away from home incurs significant monetary and welfare costs. While adjustments in home presence during workdays are less costly, these subtle changes can have important labor market implications if accumulated over time.

A small set of recent studies have examined home presence and travel behaviors for avoiding wildfire smoke. Most of these studies use cell phone mobility data (e.g. Safegraph) to track how exposure to smoke affects time spent at home and out-of-county travel. For example, Burke et al. (2022) study how the percentage of users staying at home the entire day changes due to smoke exposure; when PM2.5 is above 50 μg/m^3, the number of individuals in the data spending their day at home increases by about 10% on average. Holloway and Rubin (2022) use Safegraph data to study out-of-county travel in response to smoke. They find that the share of sites visited outside users' home county increases by 0.28 percentage points on average during weeks when their home county was exposed to smoke, an increase of about 1.3 percent above baseline. Both Burke et al. (2022) and Holloway and Rubin (2022) find that avoidance adaptation is increasing in Census block group household income.

While cell phone tracking data has many useful characteristics, datasets made available to researchers are generally aggregate data, which come with some downsides. Safegraph provides data on the share of users observed to have stayed entirely at home on a given day at the Census block group level. It is not possible to observe from these data changes in time spent at home, or the times of day at which time spent at home is more likely to increase. Moreover, these data do not allow inclusion of user fixed effects. If users with particular patterns of home occupancy are more likely to live in areas affected by wildfire smoke, estimates based on aggregate data could be biased. For example, rural areas, which may be more likely to be affected by wildfire smoke, are also older on average, and older residents may have different capacities and/or needs to modify their behavior in response to smoke[1]. Safegraph also provides data on the number of visits to selected places of interest (POIs), and the counties that visitors are from. Holloway and Rubin (2022) use these data to measure changes in out-of-county travel in response to smoke, but because the data are not at the individual level, it is not possible to discern whether users overall number of visits to POIs changes when they travel out-of-county.

More broadly, our findings also connect to an emerging literature on the economic impacts of wildfire smoke. This includes effects on credit card and mortgage defaults, as well as property and rent values (An et al., 2023; Addoum et al., 2199; Lopez and Tzur-Ilan, 2023).

Our findings have important policy implications for mitigating impacts of wildfire smoke. First, the observed heterogeneity in avoidance behaviors underscores the need for targeted outreach to demographic groups that are less likely to engage in protective actions, such as renters or individuals with less flexibility in their daily schedules. This could involve tailored public health campaigns or assistance programs aimed at promoting protective behaviors. Second, our results highlight the value of high-frequency, individual-level data in designing and evaluating interventions aimed at reducing pollution exposure. This information can inform more effective urban planning and disaster response strategies, helping communities better adapt to the growing risks associated with wildfire smoke.

2 Data

2.1 Smart-Thermostat

We measure time spent at home using smart-thermostat data from Ecobee, a major smart thermostat company. Ecobee collects anonymized data from users who voluntarily participate in its Donate Your Data program to share with researchers.[2] This dataset contains high frequency data (at five minute intervals) for every participating household in its database, providing measures of temperature, thermostat setting, and whether someone is at home as detected by one or more motion detection sensor(s).

For our analysis, we restrict the sample to all 6,153 households in California in our data. To obtain more precise location of the household, we match each household's city in the database to census place using a fuzzy match based on the recorded city name. Figure A1 shows the geographic distribution of users by county, with the color indicating the number of users on the left panel and the density of users on the right. There are users in most parts of California, except for Northern California and the central Sierra region. More users

[1] `https://www.census.gov/newsroom/blogs/random-samplings/2016/12/a_glance_at_the_age.html`

[2] See `https://www.ecobee.com/en-us/donate-your-data/` for more details on the program.

reside in populous areas such as the Bay Area and Southern California - their distribution is largely reflective of the underlying population. Nevertheless, it is important to note that smart thermostat users likely differ from general population significantly in socioeconomic conditions. Unfortunately, as the data do not contain demographic variables, we cannot quantitatively assess these differences.

Each Ecobee household in our final sample has at least one motion detection sensor that is attached to the main thermostat and some households also install additional remote sensors. The data contains five-minute readings from these sensors. For tractability, we collapse the data to the half-hourly level. The motion sensors can take either TRUE or FALSE values, conditional on the value being non-missing. If any one motion sensor recorded a "TRUE" value in a half-hour block, a user was classified as being at home (indoors) in that block[3]. Figure A2 shows the daily pattern of minutes at home by weekday/weekend in the left panel, and by season in the right. In general, the detected activity level is the lowest between midnight and early morning due to reduced movement as most people are sleeping. Activity ramps up significantly between 5 to 7 a.m., then displays a U-shape during 7 a.m.–6 p.m., and finally falls again after 8 p.m. To remove noise from periods of low movement, we exclude nighttime data from our analysis. People spend substantially more time at home during daylight hours over weekends than weekdays, and slightly less time during the evening hours. The differences across seasons are less remarkable, with people spending slightly more time at home during winter and spring. Overall, these patterns are consistent with the typical work and recreation schedule of a household, suggesting that the data is reflective of users' time use behavior.

Based on the half hourly data, we then construct two main outcome variables. Our first outcome variable is time spent at home during work (8 a.m. - 5 p.m.) and non-work (5 p.m. - 8 p.m.) segments. We divide the total number of half-hours a user is home by the total number of half-hours observed to get the proportion of time a household is home i.e. indoors. Multiplying the calculated proportion by hundred gives our measure of "percentage time spent at home". Our second outcome variable measures whether users choose to vacate their residences temporarily or not on any given day. For a user to be away from home on any day, the sensors should record "FALSE" for all half-hour blocks in that day. If a user is away for at least 2 days in a row, we classify the first day of such a sequence as the first day of temporary residence vacancy. Table A1 provides summary statistics on these measures.

The Ecobee dataset consists of 6153 households in California. 105 households are in cities for which we do not have data on PM2.5, hence, they are dropped from our sample. Of the remaining, 6043 households, 1255 households have more than 5 percent of entirely missing

[3]The sensors do no capture movements by pets.

days. These households are likely those with the older Ecobee models that do not come with sensors. After removing them, we are left with 4793 households. Of these, 2010 households have discontinuous daily data. On dropping days with less than 10 days in the initial and end periods for each household that causes discontinuity in data, we are able to retain 74 households, leaving us with a final sample of 2857 households.

2.2 Smoke Day

Our preferred definition of smoke days is based on a combination of smoke plume and air pollution data. The smoke plume data has two important limitations. They cannot distinguish between smoke high in the air column and smoke impacting surface air quality, and they also may not recognize smoke plumes concealed by cloudy days (Childs et al., 2022). To address these limitations, we supplement the smoke plume data with PM2.5 daily summary data. Using the combined data, we define smoke days as those days when there is presence of smoke plume and the PM2.5 level exceeds a predetermined threshold. This definition allows us to focus on wildfire smoke that induces elevated ground-level air pollution exposure. Figure A3 shows the distribution of user-days across different smoke day categories in our data.

For smoke plume, we obtain data from NOAA's Hazard Mapping System (HMS) Fire and Smoke Analysis product. Starting in 2005, the NOAA HMS program has identified the spatial extent of smoke plumes in the US on a daily basis. The data is constructed from twice-daily visible and infrared geostationary satellite observations (NASA Geostationary Operational Environmental Satellites, GOES) using an automated, manually quality-controlled process (Rolph et al., 2009). Smoke plumes are also categorized light, medium or heavy density based on thickness of the smoke. The result of the analysis is a series of polygon shapefiles identifying locations where smoke has been observed in the air column each day. We use these data to construct a daily indicator variable for whether smoke plumes were present at each census place on each day within our sample period[4]. We use census place polygons to define place boundaries, and designate the place has having been affected by smoke on a given day if the place intersected any smoke plumes on that day, regardless of density.

We extracted PM2.5 daily summary data from EPA's Air Quality System (AQS) database for monitors in California and its neighboring states: Arizona, Nevada and Oregon. To construct a balanced panel of census places, we matched each place polygon in California

[4]Classifying smoke into categories such as none, light, medium, and heavy involves considerable uncertainty. The recommended practice is to avoid detailed classifications; therefore, we use only the presence of smoke as our variable.

(ACS 2013-2017) with monitors located within 20 miles using nearest neighbor matching[5]. We determined the PM record for every place-date combination as a weighted PM measure by calculating weights using inverse distance weighting, where j represents the census place, t denotes the day, m is the matched monitor, and w is the inverse weight:[6].

$$P\bar{M}2.5_{jt} = \frac{\sum_{m \in \mathcal{M}_j} w_i PM2.5_{mt}}{\sum_{m \in \mathcal{M}_j} w_i}$$

Figure A4 shows the distribution of distance between each user's city centroid and its matched monitor(s), weighted using the same scheme. For the vast majority of the users, the weighted distance falls within 5 miles.

2.3 Weather

Our weather measures come from PRISM Climate Data (Oregon State University, 2023). This is a nationwide gridded data with approximately 4km resolution containing daily weather observations. For every census place, we extracted daily mean temperature (in degrees Celsius) and precipitation (in millimeters) using its centroid.

2.4 Demographics and Predicted Home Values

To examine heterogeneous responses from different demographic groups, we obtain demographic data from the 2013-2017 American Community Survey at the Census place level, including family income, the share of White population, and the share of college graduates.

We also construct a measure of predicted home values for each user based on their home square footage, age, and city as reported in the Ecobee data. To generate this measure, we first create a model of log home prices as a function of log square footage, building age, year of sales. We estimate this model for each Census place or city using home transactions data from Zillow's Transaction and Assessment Database (ZTRAX).[7] The city-specific model is then combined with input from the Ecobee user data to predict their home values.[8] It should

[5]For comparability in PM records, we used monitors with parameter codes 88101 and 88502. 88101 monitors use Federal Reference Methods (FRM) and 88502 are "FRM-like".

[6]weight $= \frac{1}{(1+miles)^2}$. Inverse distance weighting is used for all monitors.

[7]Property assessment and transaction data were provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at `http://www.zillow.com/ztrax`. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group. In accordance with the ZTRAX Access Agreement, we have deleted raw ZTRAX data and only retained the city-specific model coefficients.

[8]For a small number of users whose home built year is missing, we repeat these steps using a model without building age. We do not predict a home value if the square footage is missing.

be noted that we interpret this measure as a proxy for the users' socioeconomic conditions rather than an accurate estimate of their property values.

3 Empirical Design

We estimate Ecobee users' response to wildfire smoke using the following specification for proportion of time spent at home:

$$Y_{ijt} = \beta \cdot \mathbb{1}(SmokeDay^{\zeta}_{jt}) + \mathbf{X}'\theta + \phi_{id(t)} + \eta_{w(t)} + \epsilon_{ijt} \quad (1)$$

Y_{ijk} is the proportion of time spent at home for user i in city j on day t during work (8 a.m. - 5 p.m.) and non-work (5 p.m. - 8 p.m.) hours[9]. The key regressor $\mathbb{1}(SmokeDay^{\zeta}_{jt})$ is an indicator variable which equals to one when there is presence of smoke plume in the air column and the ground level PM2.5 is greater than or equal to ζ $\mu g/m^3$ in city j on day k. We specify ζ to take values of both 12 μg/m^3 and 35 μg/m^3. According to World Health Organization guidelines, PM2.5 concentrations above 35 μg/m^3 are unhealthy for sensitive groups; below 35 μg/m^3, PM2.5 concentrations are considered "moderate." As well, the EPA National Ambient Air Quality daily standard for PM2.5 is set at 35 μg/m^3.[10] Hence, we use $\mathbb{1}(SmokeDay^{35}_{jt})$ with the main regressor as our preferred specification.

The vector of controls which includes a national holiday dummy and polynomials to the second degree of temperature and precipitation is X. $\phi_{id(t)}$ is a user-by-day-of-week fixed effect to capture the unique time use pattern of each user. $\eta_{w(t)}$ is a week-of-sample fixed effect. Given that smoke plumes can be present in varying heights in the air column, it is important to combine it with measures of ground PM2.5 to isolate effective smoke days. Additionally, while the baseline level of PM2.5 may be endogenous, occurrence of wildfire smoke is exogenous. By using the presence of both smoke plumes on an elevated PM2.5 day, β provides a causal estimate of the users' response to wildfire smoke. In other words, there is no unobservable factor that drives both a smoke day and people's time use behavior. For example, this assumption may be violated when people are traveling more during a holiday or less during the Covid shutdown period. To address these concerns, we control for national holiday and exclude 2020 and beyond from our sample.

[9] Some half-hour blocks have missing observations, where the sensor did not indicate whether the user was home or not. To avoid misclassification, we calculate the proportion of hours spent at home based on the hours observed.

[10] Under the Clean Air Act, an area falls out of compliance with the Clean Air Act if 24-hour air quality falls below 35 μg/m^3 more than 2 percent of days per year over a three-year period. However, days on which smoke causes air quality to fall below this threshold can generally be excluded from assessments of regulatory compliance under the Clean Air Act's Exceptional Events Rule.

To examine whether households travel away from their homes as a pollution avoidance strategy, we use the following specification:

$$Y_{ijt} = \beta \cdot \sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_{j\tau}^{\zeta}) + \mathbf{X}'\theta + \phi_{id(t)} + \eta_{w(t)} + \epsilon_{ijt} \tag{2}$$

Here, the outcome is whether user i in city j vacate their home on day t, as defined in Section 2.1. The sample excludes the following days when they are away. The key regressor $\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_{j\tau}^{\zeta})$ is the number of days there is both smoke plume and the PM2.5 is greater than or equal to ζ $\mu g/m^3$ in the previous seven days. As before, we specify ζ to take values of both 12 μg/m^3 and 35 μg/m^3. This measure is intended for representing variation in smoke days over a longer period. As traveling from home is a costlier avoidance strategy, we expect this decision to be motivated by a prolonged period of wildfire smoke pollution. The other controls are the same as before, as is the identification assumption.

Throughout the analysis, we cluster the standard error at the census place level to account for correlations between users in the same city and over time.

4 Results

Table A1 shows the proportion of time that people spend in the home on different days of the week and their likelihood of leaving their home. On weekdays, people spend a lower percentage of time at home in the morning but a higher percentage in the evening compared to weekends. The chances of vacating residence is highest on Friday and Saturday. These patterns show that weekday mornings accords users the largest margins in adjusting the time spent at home. Users experience smoke on roughly 8 percent of days (Figure A1).

4.1 Pollution and Time Spent at Home

Table 1 reports the results on percent time spent at home during weekdays. Column (1) presents the estimates for day time (8 a.m.–5 p.m.), which suggest that a day with smoke plume is associated with a 0.48 percentage point (p.p.) (about 2.6 minutes) increase in time spent at home on average, equivalent to a 0.85 percent increase when compared to the outcome mean. Column (2) shows the results of our preferred specification. The estimate in column (2) implies that a day with smoke plume and high PM2.5 leads users to spend 2.25 p.p. more time at home on average (about 13.5 minutes), or 3.98 percent of the mean time spent at home. In column (3), we also find that users spend more time at home on a smoke day with moderate to high PM2.5 level (exeeding 12 μg/m^3), but as expected, the effect is

Table 1: Wildfire Smoke and Time Spent at Home During Weekdays

	Dependent variable: Percentage Time at Home					
	Day Time (8 a.m. - 5 p.m.)			*Evening Time (5 p.m. - 8 p.m.)*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(SmokePlume)$	0.485***			-0.052		
	(0.142)			(0.139)		
$\mathbb{1}(SmokeDay^{35})$		2.251***			1.573***	
		(0.408)			(0.347)	
$\mathbb{1}(SmokeDay^{12})$			0.443**			0.275
			(0.208)			(0.173)
Precipitation	0.090***	0.091***	0.090***	0.039***	0.040***	0.039***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
$(\text{Precipitation})^2$	-0.001***	-0.001***	-0.001***	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	0.057	0.072	0.062	0.086	0.094	0.086
	(0.076)	(0.076)	(0.076)	(0.058)	(0.058)	(0.058)
$(\text{Temperature})^2$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Holiday	6.700***	6.719***	6.700***	-4.527***	-4.514***	-4.525***
	(0.235)	(0.235)	(0.235)	(0.191)	(0.190)	(0.192)
Mean	56.5	56.5	56.5	71.43	71.43	71.43
User by Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,346,392	1,346,392	1,346,392	1,335,638	1,335,638	1,335,638
R^2	0.432	0.432	0.432	0.325	0.325	0.325

Notes: This table contains results from estimation of Equation (1) for time spent at home on weekdays. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. The dependent variable is the percentage of time a user was home each day during the defined time windows. Number of half hour blocks the user was home divided by the observed number of half hour blocks times 100 gives the percentage of time a user was home. Standard errors are clustered at the census place level.

Table 2: Time Spent at Home by Quintiles of Baseline Time Use

	Q1	*Q2*	*Q3*	*Q4*	*Q5*
A. Day time (8 a.m. - 5 p.m.)					
$\mathbb{1}(SmokeDay^{35})$	2.267***	1.269	4.341***	2.348***	0.704
	(0.732)	(1.016)	(0.817)	(0.857)	(0.581)
Mean	25.7	42.87	56.52	68.79	81.82
Observations	232,961	266,590	273,671	284,899	288,271
R^2	0.186	0.117	0.088	0.078	0.123
Controls	Yes	Yes	Yes	Yes	Yes
B. Evening time (5 p.m. - 8 p.m.)					
$\mathbb{1}(SmokeDay^{35})$	0.655	1.684*	2.054***	2.292***	0.889
	(1.335)	(1.008)	(0.765)	(0.665)	(0.630)
Mean	41.72	62.73	73.71	81.72	90.42
Observations	227,269	261,856	271,691	287,067	287,755
R^2	0.152	0.066	0.060	0.060	0.074
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table contains results from estimation of Equation (1) for time spent at home on weekdays by users divided into quintiles based on their mean time spent at home. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. The dependent variable is the percentage of time a user was home each day during the defined time windows. Number of half hour blocks the user was home divided by the observed number of half hour blocks times 100 gives the percentage of time a user was home. Standard errors are clustered at the census place level. *p<0.1; **p<0.05; ***p<0.01.

smaller in magnitude.

In columns (4)-(6), we use the same specifications to examine evening time spent at home (5 p.m.–8 p.m.). Here, the estimate is also positive and statistically significant for our preferred specification but lower by approximately 1 p.p. In general, the response in evening hours is weaker, possibly because people already spend most of weekday evening hours at home and there is less room for adjustment.

We also examine differential responses from users who routinely spend different amount of time at home. In Table 2, we divide users into different quintiles of baseline time spent at home and separately estimate their changes in time spent at home on smoke days. We find the strongest responses from the middle of the distribution, perhaps because these users have more flexibility in their time use when compared to users who spent the least or most time at home on a regular basis.

Overall, we find evidence that people increase their time spent at home during the day on weekdays when air pollution reach high levels due to wildfire smoke. This is consistent with a motivation to avoid exposure.

4.2 Pollution and Traveling Away from Home

Table 3: Wildfire Smoke and Travelling Away from Home

	Dependent variable: Vacated Residence		
	(1)	(2)	(3)
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokePlume_{\tau})$	0.027^{***}		
	(0.008)		
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay^{35}_{\tau})$		0.065^{***}	
		(0.020)	
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay^{12}_{\tau})$			0.013
			(0.009)
Temperature	0.030^{***}	0.035^{***}	0.033^{***}
	(0.010)	(0.010)	(0.010)
$(\text{Temperature})^2$	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0003)	(0.0002)	(0.0002)
Precipitation	0.004^{*}	0.004^{*}	0.004^{*}
	(0.002)	(0.002)	(0.002)
$(\text{Precipitation})^2$	-0.0001^{**}	-0.0001^{**}	-0.0001^{**}
	(0.00004)	(0.00004)	(0.00004)
Holiday	0.394^{***}	0.397^{***}	0.394^{***}
	(0.047)	(0.047)	(0.047)
Mean	0.57	0.57	0.57
Week-of-sample FE	Yes	Yes	Yes
User by Day of week FE	Yes	Yes	Yes
Observations	1,898,888	1,898,867	1,898,867
R^2	0.041	0.041	0.041

Notes: This table represents results from estimation of Equation (2). The dependent variable is an indicator for first day of leaving home. It takes a value 1 on the first day of the user vacating residence and 0 on all non-vacation days. Column (1) uses the number of days with smoke plume in the last 7 days as the main variable of interest. Column (2) uses the number of smoke days with PM2.5 $\geq$ 35 µg/m^3 in the last 7 days as the main variable of interest. Column (3) uses the number of smoke days with PM $\geq$ 12 µg/m^3 as the main variable of interest.Standard errors are clustered at the census place level.

Next, we examine another avoidance behavioral margin: whether people leave their homes and travel elsewhere to avoid smoke pollution. Table 3 reports the main estimates from Equation (2)on the effect of wildfire smoke in the previous 7 days on whether the household vacate their residence.

We find positive and statistically significant estimates for both days with the presence of smoke plume and those with both smoke and high PM2.5 in columns (1) and (2). Our preferred estimate in column (2) indicates that an additional day with smoke plume and high PM2.5 among the previous 7 days increases the probability of vacating residence by 6 basis points (b.p.). To put this magnitude in context, the effect is equivalent to a 11.4% of the mean probability of vacating residence. Smoke days with moderate PM2.5 in column (3) also shows an increase by 1 basis point but the effect is not significant.

Our results provide substantial evidence in support of short-term avoidance behavior in response to wildfire induced pollution by individuals. They align with the existing work on wildfire induced pollution avoidance behavior that also suggest that people spend more time at home on smoke plume days with high PM2.5. We are able to provide more detailed estimates based on the time of day when individuals engage in said avoidance. We find that most of the effect is driven by altering time at home during day time hours as opposed to evening hours. Furthermore, these avoidance behaviors are more evident during weekdays as opposed to weekends.

4.3 Heterogeneous Effects

Households with different characteristics might have different behavioral responses to wildfire smoke due to differences in their ability to adjust time use and financial resources for travel (Holloway and Rubin, 2022; Burke et al., 2022). We explore these potential heterogeneous responses by splitting the sample of users along several key socio-economic dimensions and separately estimating the effect of wildfire-induced pollution on the two main outcomes under our preferred specification.

In Table 4, we examine three demographic variables of the users' Census place. Column (1) presents estimates from users living in Census place where family income is below median, while column (2) shows those above median.[11] We find a larger increase in percent of time at home during weekday day time for users from lower-income communities when compared to their counterparts from higher-income ones, but a reverse pattern for vacating residence. We observe somewhat similar pattern in columns (5)-(6) where users in more educated communities respond marginally lesser in hours at home but more in traveling away from home. When we split the sample by the share of White population in columns (3)-(4), we find that users in more White places are more responsive in increasing time spent at home and also more likely to vacate residence. These patterns are indicative of different avoidance strategies and behavioral adjustments taken by different demographic groups. In particular, we consistently find that users from more marginalized communities (i.e. lower-income, less White and educated) are significantly less likely to travel away from home, which might require significant financial means and flexibility.

An important limitation of these results, however, is that the aggregate demographics of the Census places might not be representative for Ecobee users. To address this problem, we

[11] The median refers to the sample median, not the median income of California.

Table 4: Heterogeneous Responses Based on Census Place Demographics

	Family Income 88023		White Population 0.62		Bachelors or More 0.36	
	≤ Median	*> Median*	*≤ Median*	*> Median*	*≤ Median*	*> Median*
A. Percentage time at home between 8 a.m. - 5 p.m.						
$\mathbb{1}(SmokeDay^{35})$	2.923***	1.844***	1.669***	3.285***	2.338***	2.036***
	(0.541)	(0.496)	(0.494)	(0.490)	(0.607)	(0.518)
Mean	55.18	57.72	55.53	57.48	55.95	57.02
Observations	647,536	698,856	678,432	667,960	660,373	686,019
R^2	0.443	0.420	0.413	0.451	0.436	0.428
Controls	Yes	Yes	Yes	Yes	Yes	Yes
B. Vacated residence						
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_{\tau}^{35})$	0.043	0.072***	0.060**	0.078***	0.065*	0.076***
	(0.032)	(0.026)	(0.029)	(0.029)	(0.034)	(0.025)
Mean	0.54	0.59	0.56	0.57	0.49	0.64
Observations	913,430	985,437	954,266	944,601	938,119	960,748
R^2	0.046	0.036	0.034	0.048	0.043	0.039
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table contains estimates from sub-samples of users residing in places with below and above median family income, proportion of white population and proportion of individuals with bachelors or a higher degree. The dependent variable is time spent at home on weekdays in Panel A and leaving home in Panel B. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. Standard errors are clustered at the census place level.

next examine a user-specific characteristic – predicted home value. While we do not directly observe users' demographics, the Ecobee data record the square footage and age of the users' homes, which we use to predict their property values as described in Section 2.4.

Predicted home values provides us with user-level variation in a proxy for household wealth. We examine variation in avoidance behavior of households below and above the sample median of predicted home value (columns 1 and 2, respectively, of Table 5) and below and above the median predicted home value in each user's own county (columns 3 and 4). The percentage increase in time spent at home is similar among higher and lower value home users when the sample is divided based on the sample median. This follows the same pattern as suggested by columns (1) and (2) in panel A in 4. However, the county median split shows a stronger response in increasing time spent at home among users with a higher predicted home value. On smoke and high pollution days, they increase the percent of time spent at home by 2.68 p.p. as opposed to 1.84 p.p. for those living in lower-valued homes.

When splitting the sample based on either the sample median or the within-county median, we find that users in higher-value homes are more likely to vacate their residences. The

Table 5: Heterogeneous Responses Based on Predicted Home Value

	Home Value			
	≤ Median	*> Median*	*≤ County Median*	*> County Median*
A. Percentage time at home between 8 a.m. - 5 p.m.				
$\mathbb{1}(SmokeDay^{35})$	2.332***	2.025***	1.840***	2.677***
	(0.597)	(0.587)	(0.630)	(0.492)
Mean	54.93	58	54.05	58.93
Observations	612,856	663,127	629,565	646,418
R^2	0.446	0.410	0.432	0.419
Controls	Yes	Yes	Yes	Yes
B. Vacated Residence				
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_{\tau}^{35})$	0.052	0.076***	0.045	0.084***
	(0.032)	(0.026)	(0.029)	(0.030)
Mean	0.5	0.63	0.53	0.61
Observations	863,581	935,795	885,560	913,816
R^2	0.047	0.036	0.036	0.044
Controls	Yes	Yes	Yes	Yes

Notes: This table contains estimates from sub-samples of users with predicted home values below and above the sample median (columns (1) and (2)) and the county median (columns (3) and (4)). The dependent variable is time spent at home on weekdays in Panel A and leaving home in Panel B. Home values are predicted using square footage and age. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. Standard errors are clustered at the census place level.

probability of traveling away from increases by 7.6-8.8 b.p. for an additional smoke and high PM2.5 day in the past seven days, compared to a much smaller and statistically insignificant increase for their peers.

In conclusion, the average estimated effects in the previous sections mask important heterogeneity in the responses. Our findings consistently show that households living in higher-income, more White and educated communities as well as those with higher-value homes have a stronger avoidance response to high particulate matter pollution due to wildfire smoke by traveling away from home. In terms of time spent at home, we find that users in marginalized communities adjust more.

4.4 Robustness

We conduct several robustness checks of our main results.

First, we test the robustness of our result against the confounding effect of evacuation from an active fire nearby. If an active wildfire nearby leads to evacuation notices which in turn changes the time spent at home and decisions to vacate residence, our estimate would reflect not only avoidance of smoke but also direct wildfire impacts, as the two are correlated. To alleviate this concern, we conduct a simple robustness check by dropping user-days with active wildfires within 5 miles from our sample. Tables A2 and A3 report these results, which remain very similar to our main ones regarding the general direction and magnitude.

Second, the main results remain robust when controlling for year-month fixed effects, as opposed to week-of-sample fixed effects, as demonstrated in Tables A4 and A5 in the appendix.

Third, a regression including an interaction between the PM2.5 indicator and the smoke variable reveals that days characterized by both high pollution and smoke lead to the largest increase in time spent at home (Table A6).

5 Comparison between avoidance measures

Our results provide evidence regarding two channels through which households reduce exposure to wildfire smoke: by increasing time spent at home, and through temporary travel away from home, presumably to higher air quality locations. Which of these strategies is of greater consequence for reductions of smoke and PM2.5 exposure depends on the extent of uptake and the extent to which the strategy results in reductions in exposure. To compare reduced exposure due to intensive and extensive margin avoidance, we perform a back-of-the-envelope calculation in which we calculate changes in the number of hours individuals were exposed to smoke plume and PM2.5 greater than 35 μg/m^3 as a result of each strategy. For time spent at home, we calculate the reduction in exposure hours (ΔH^1) as:

$$\Delta H^1 = \sum_t \sum_j \mathbb{1}(\text{weekday}) \cdot \phi \cdot \overline{SmokeDay^{35}_{jt}} \cdot N_j \cdot \left(\frac{9\beta^{\text{D,Weekday}}}{100} + \frac{3\beta^{\text{E,Weekday}}}{100}\right) \tag{3}$$

where N_j is the count of households in our sample in place j and ϕ is a parameter representing the share of time spent away from home individuals are assumed to spend outdoors. $\beta^{D,Weekday}$ represents estimated average change in the percent of time spent at home during daytime hours (D) on weekdays and $\beta^{E,Weekday}$ during evening hours (E). Though indoor PM levels can vary widely, we assume for the purpose of this exercise that on when days PM2.5 is above 35 μg/m^3 outdoors, it is below this threshold in indoor locations. We find that users in our sample avoid 1340 hours of exposure to smoke-high PM2.5 per year by increasing time spent at home.

For temporarily vacating smoke-impacted areas, we calculate the reduction in exposure hours (ΔH^2) as:

$$\Delta H^2 = \sum_t \sum_j \mathbb{1}\big(SmokeDay_{jt}^{35}\big) \cdot \beta \cdot \mu \cdot N_{jt} \cdot \phi \cdot \big(9(1-\bar{Y}^{D,d(t)}) + 3(1-\bar{Y}^{E,d(t)}) + 12\big) \quad (4)$$

Here, β represents the change in the probability a household will choose to leave home due to high PM2.5 levels, μ represents the median number of days away from home for households who leave, N_{jt} represents the number of households in the sample at place j, and ϕ again represents the share of time individuals are assumed to spend outdoors. The final term in equation 4 provides the average number of hours that a household spends outside the home on a given day, which we assume is also representative of days on which the household has left the area. We find that users in our sample avoid 1414.93 hours by vacating residences.

6 Conclusion

We find that individuals engage in avoidance behavior by increasing time spent at home and by traveling away from home to avoid wildfire smoke pollution. The increase in time spent at home is particularly evident during weekday daytime hours, when users may have greater margin to adjust their time spent at home. The estimates indicate that smoke days with high PM2.5 ($\geq 35\mu$g/m^3) increases the share of time spent at home by Ecobee users during weekday daytime hours by 2.25 percentage points on average—a 3.98 percent increase above users' baseline average.

Users are also more likely to spend a day or more away from home during periods of heavy air pollution due to smoke. We find that whereas on any given low pollution day the likelihood typical household leaves home for more than a day is 0.56 percentage points, this probability increases by 6 basis points on high pollution days caused by smoke.

While these behaviors are undertaken voluntarily in order to minimize health and other consequences from smoke, they are nevertheless costly, and some populations may be better able to bear these costs than others. We find that smoke causes users with predicted home value (based on square footage and age) above the county median to more strongly increase the amount of time at home during day time hours, and to more substantially increase the likelihood of leaving home for more than one day, than for users living in homes with below median home value.

A key limitation of our study is that the data are drawn from users with smart thermostats, who are likely to be wealthier than California's broader population and thus not fully representative.[12] Previous studies have used cellphone tracking data, which, due to the greater penetration of smartphone use in the overall population, is more broadly representative. However, while available cellphone data provides some information at the level of individual user, it is generally not possible to track users over time, nor do these data provide information about how time spent at home changes over the course of the day. In contrast, smart thermostat data allows us to track individual households' behavior at a fine temporal scale, enabling use of household-level fixed effects and allowing us to analyze the times of day and times of week when smoke changes behavior the most. We therefore view our study as a complement to these previous studies.

While this and related studies have consistently demonstrated that, in the face of significant degradations in air quality due to smoke, populations engage in costly avoidance behavior to a significant degree, there is currently little work available quantifying these costs. This is an important area for future research, which could enable inclusion of avoidance costs in estimates of overall damage costs associated with smoke. A second important area for future research is more detailed examination of behavior of smoke exposure and the capacity for avoidance behavior within disadvantaged groups. While our study and previous studies have typically pursued heterogeneity analyses using aggregate data (our estimated home value analysis is an exception), these data may mask heterogeneity at the individual or household levels. Therefore, there is a need for researchers to identify new data sources that would enable understanding responses to smoke within disadvantaged groups at the individual level.

[12]These data also limit the interpretation of our heterogeneity analyses, which must be viewed as studies of heterogeneous responses among the population of Ecobee users, rather than of heterogeneous responses within the population overall.

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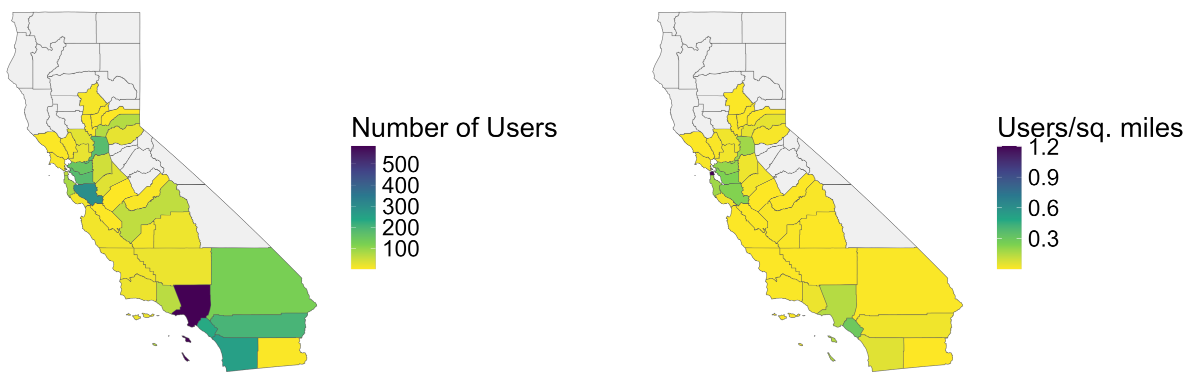
A Appendix

A.1 Descriptive Statistics

Table A1: Percentage Time at Home and Probability of Vacating Residence

	Days	Time at home (Morning)	Time at home (Evening)	Prob(vacate)
1	Monday-Thursday	54.76	70.62	0.006
2	Friday	56.78	66.59	0.008
3	Saturday	65.26	63.35	0.010
4	Sunday	65.82	69.61	0.007

Notes: time at home was calculated for each user-day group pair and then averaged across users. Trip days including the day prior to leaving was not included in the calculation. Probability of vacating residence was based on first day of leaving home divided by the total number of non-trip days.



Number of Users in Each County **Number of Users Per Square Mile**

Figure A1: Comparison of User Metrics Across Counties

Note: The left panel shows the total number of our final sample users in each county. The right panel adjusts for county size by showing the number of users per square mile.

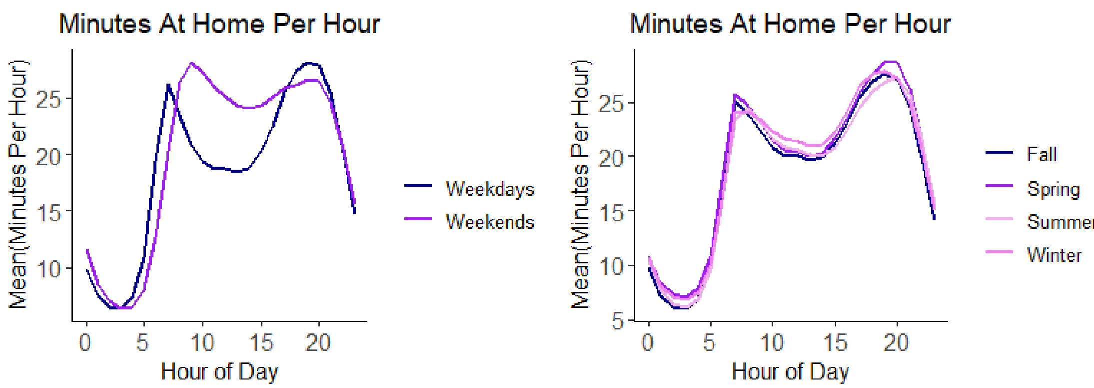


Figure A2: Daily Patterns of Minutes at Home per Hour
Note: The left panel shows the average number of minutes spent at home per hour across the day, comparing weekdays and weekends. The right panel displays seasonal patterns in time spent at home.

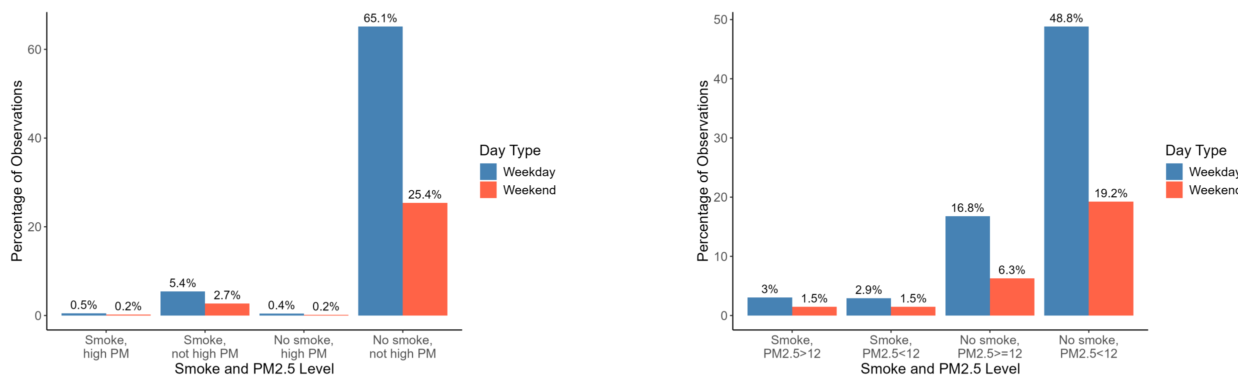


Figure A3: Distribution of User Days by Smoke Days
Note: The figure on the left panel shows the distribution of user days across days with different smoke and PM2.5 levels exceeding 35 $\mu g/m^3$. The figure on the right panel shows the distribution of user days across days with different smoke and PM2.5 levels exceeding 12 $\mu g/m^3$

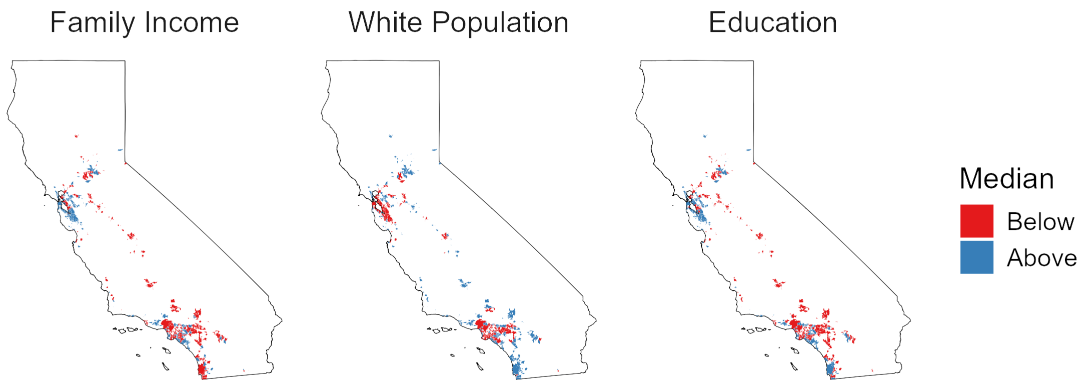


Figure A5: Distribution of Places by Demographics

Note: Each map displays the spread of census places in California categorized as above or below the statewide median for a specific demographic characteristic. The first map shows the distribution by median family income, the second by the share of non-Hispanic white population, and the third by the share of adults with a bachelor's degree or higher.

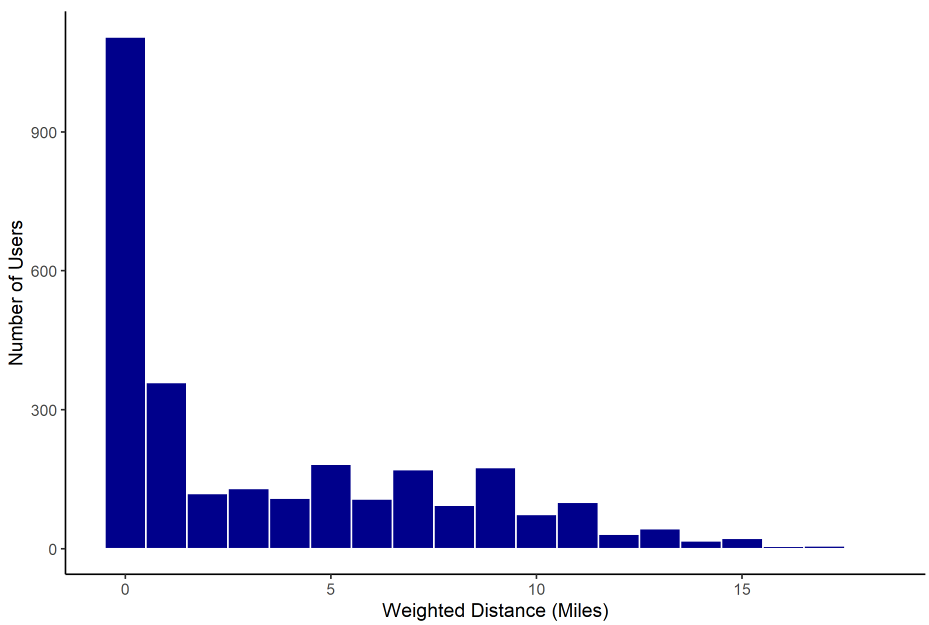


Figure A4: Distribution of Weighted Distance Between Monitors and User Cities

Note: This figure shows the distribution of weighted distances between air quality monitors and users in miles. The majority of users are located very close to their assigned monitor, with over 900 users within the first mile. The frequency of users declines sharply as distance increases, indicating that most users are matched to nearby monitors.

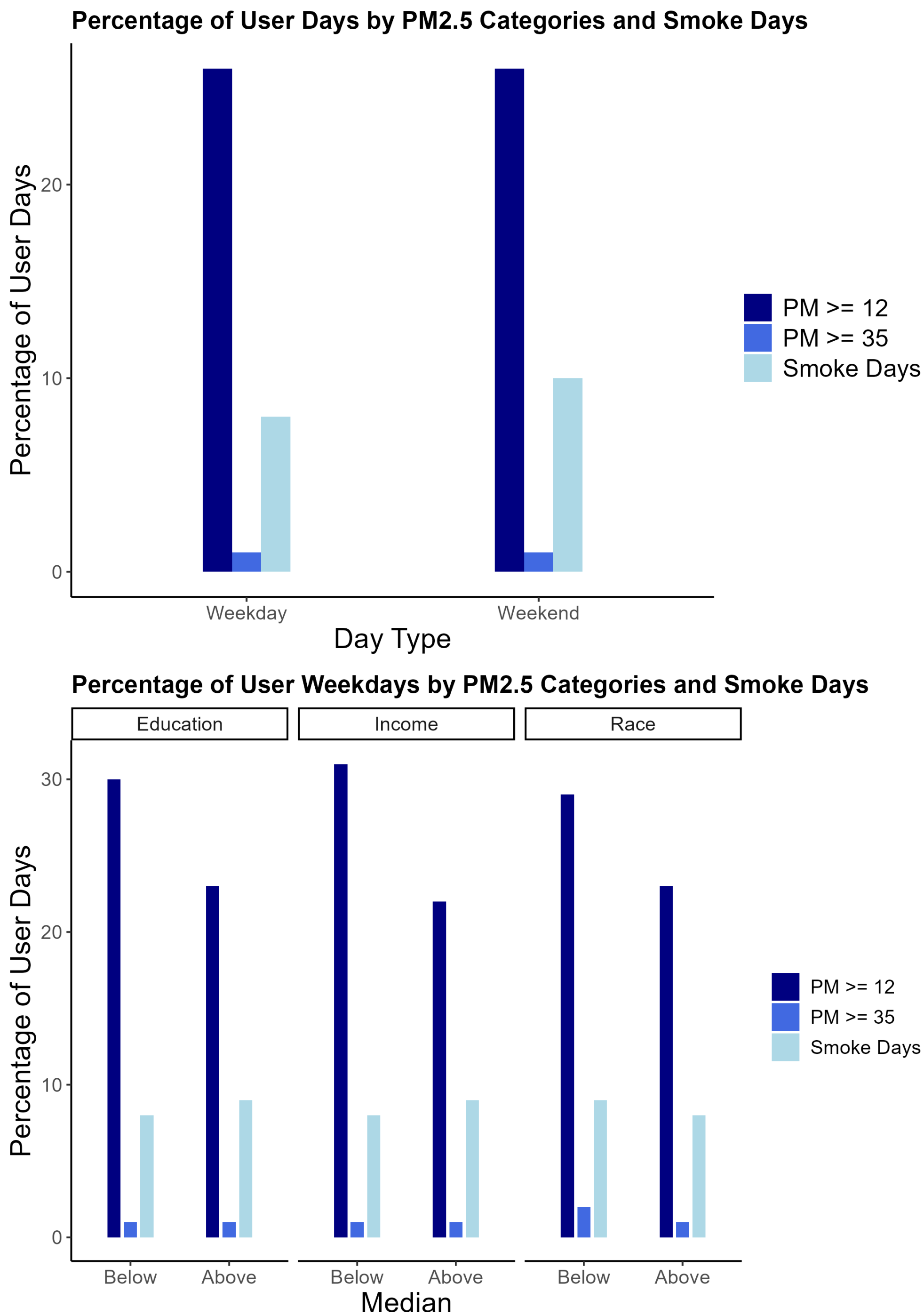


Figure A6:

Note: The statistics in this figure has been calculated using days the users did not vacate their residences. PM $\geq$ 12 corresponds to days PM2.5 was at least 12 $\mu g/m^3$ but less than 35 $\mu g/m^3$. PM $\geq$ 35 corresponds to days PM2.5 was at least as high as 35 $\mu g/m^3$. The figure in the bottom panel is filtered to include only weekdays.

A.2 Additional Tables

Table A2: Robustness Check Excluding Nearby Fire - Time Spent at Home

	Dependent variable: Percentage Time at Home					
	Day Time (8 a.m. - 5 p.m.)			*Evening Time (5 p.m. - 8 p.m.)*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(SmokePlume)$	0.472***			-0.088		
	(0.126)			(0.131)		
$\mathbb{1}(SmokeDay^{35})$		2.133***			1.503***	
		(0.378)			(0.342)	
$\mathbb{1}(SmokeDay^{12})$			0.541***			0.276
			(0.186)			(0.175)
Precipitation	0.089***	0.090***	0.089***	0.038***	0.039***	0.038***
	(0.009)	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
$(\text{Precipitation})^2$	-0.001***	-0.001***	-0.001***	-0.00004	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	0.067	0.079	0.072	0.093	0.099	0.093
	(0.078)	(0.078)	(0.078)	(0.060)	(0.060)	(0.061)
$(\text{Temperature})^2$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Holiday	6.613***	6.633***	6.612***	-4.558***	-4.540***	-4.555***
	(0.231)	(0.232)	(0.232)	(0.183)	(0.183)	(0.184)
Mean	56.54	56.54	56.54	71.46	71.46	71.46
User by Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Week-of-sample FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,308,055	1,308,055	1,308,055	1,297,699	1,297,699	1,297,699
R^2	0.432	0.432	0.432	0.325	0.325	0.325

Notes: This table contains results from estimation of Equation (1) for time spent at home on weekdays. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. The dependent variable is the percentage of time a user was home each day during the defined time windows. Number of half hour blocks the user was home divided by the observed number of half hour blocks times 100 gives the percentage of time a user was home. Standard errors are clustered at the census place level.

Table A3: Robustness Check Excluding Nearby Fire - Travelling Away from Home

	Dependent variable: Vacated Residence		
	(1)	(2)	(3)
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokePlume_\tau)$	0.031***		
	(0.008)		
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_\tau^{35})$		0.070***	
		(0.020)	
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_\tau^{12})$			0.017*
			(0.009)
Temperature	0.031***	0.035***	0.033***
	(0.011)	(0.011)	(0.011)
$(\text{Temperature})^2$	−0.001***	−0.001***	−0.001***
	(0.0003)	(0.0003)	(0.0003)
Precipitation	0.004*	0.004*	0.004*
	(0.002)	(0.002)	(0.002)
$(\text{Precipitation})^2$	−0.0001**	−0.0001**	−0.0001**
	(0.00004)	(0.00004)	(0.00004)
Holiday	0.397***	0.400***	0.397***
	(0.048)	(0.048)	(0.048)
Mean	0.56	0.56	0.56
Week-of-sample FE	Yes	Yes	Yes
User by Day of week FE	Yes	Yes	Yes
Observations	1,844,742	1,844,721	1,844,721
R^2	0.041	0.041	0.041

Notes: This table represents results from estimation of Equation (2). The dependent variable is an indicator for first day of leaving home. It takes a value 1 on the first day of the user vacating residence and 0 on all non-vacation days. Column (1) uses the number of smoke plume days in the last 7 days as the main variable of interest. Column (2) uses the number of smoke days with PM2.5 $\geq$ 35 µg/$\mathbf{m^3}$ in the last 7 days as the main variable of interest. Column (3) uses the number of smoke days with PM $\geq$ 12 µg/$\mathbf{m^3}$ as the main variable of interest. Standard errors are clustered at the census place level.

Table A4: Wildfire Smoke and Time Spent at Home During Weekdays

	Dependent variable: Percentage Time at Home					
	Day Time (8 a.m. - 5 p.m.)			*Evening Time (5 p.m. - 8 p.m.)*		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(SmokePlume)$	0.533***			-0.111		
	(0.118)			(0.127)		
$\mathbb{1}(SmokeDay^{35})$		2.056***			1.289***	
		(0.372)			(0.322)	
$\mathbb{1}(SmokeDay^{12})$			0.448**			0.271*
			(0.178)			(0.149)
Precipitation	0.070***	0.072***	0.070***	0.013	0.015	0.014
	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.011)
$(\text{Precipitation})^2$	-0.0005***	-0.001***	-0.0005***	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Temperature	-0.353***	-0.344***	-0.351***	0.242***	0.249***	0.244***
	(0.058)	(0.058)	(0.059)	(0.048)	(0.048)	(0.047)
$(\text{Temperature})^2$	0.007***	0.007***	0.007***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Holiday	8.797***	8.795***	8.798***	-5.190***	-5.199***	-5.196***
	(0.268)	(0.268)	(0.268)	(0.191)	(0.191)	(0.191)
Mean	56.5	56.5	56.5	71.43	71.43	71.43
User by Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,346,392	1,346,392	1,346,392	1,335,638	1,335,638	1,335,638
R^2	0.429	0.429	0.429	0.323	0.323	0.323

Notes: This table contains results from estimation of Equation (1) for time spent at home on weekdays. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. The dependent variable is the percentage of time a user was home each day during the defined time windows. Number of half hour blocks the user was home divided by the observed number of half hour blocks times 100 gives the percentage of time a user was home. Standard errors are clustered at the census place level.

Table A5: Wildfire Smoke and Travelling Away from Home

	Dependent variable: Vacated Residence		
	(1)	(2)	(3)
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(Smoke_\tau)$	0.031^{***}		
	(0.006)		
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_\tau^{35})$		0.101^{***}	
		(0.017)	
$\sum_{\tau=t-7}^{t-1} \mathbb{1}(SmokeDay_\tau^{12})$			0.026^{***}
			(0.007)
Temperature	-0.016^{*}	-0.013	-0.015
	(0.010)	(0.009)	(0.010)
$(\text{Temperature})^2$	0.0003	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
Precipitation	0.006^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)
$(\text{Precipitation})^2$	-0.0001^{**}	-0.0001^{**}	-0.0001^{**}
	(0.00004)	(0.00004)	(0.00004)
Holiday	0.528^{***}	0.528^{***}	0.532^{***}
	(0.048)	(0.048)	(0.048)
Mean	0.57	0.57	0.57
Year-month FE	Yes	Yes	Yes
User by Day of week FE	Yes	Yes	Yes
Observations	1,898,888	1,898,867	1,898,867
R^2	0.040	0.040	0.040

Notes: This table represents results from estimation of Equation (2). The dependent variable is an indicator for first day of leaving home. It takes a value 1 on the first day of the user vacating residence and 0 on all non-vacation days. Column (1) uses the number of smoke plume days in the last 7 days as the main variable of interest. Column (2) uses the number of smoke days with PM2.5 $\geq$ 35 µg/m^3 in the last 7 days as the main variable of interest. Column (3) uses the number of smoke days with PM $\geq$ 12 µg/m^3 as the main variable of interest. Standard errors are clustered at the census place level.

Table A6: Robustness Check Using Interaction of PM2.5 and Smoke - Time Spent at Home

	Dependent variable: Percentage Time at Home	
	Day Time (8 a.m. - 5 p.m.)	*Evening Time (5 p.m. - 8 p.m.)*
PM2.5 $\geq$ 35	0.888**	-0.164
	(0.430)	(0.511)
Smoke Plume	0.349**	-0.172
	(0.140)	(0.143)
PM2.5 $\geq$ 35:Smoke Plume	1.188**	1.833***
	(0.593)	(0.634)
Precipitation	0.092***	0.040***
	(0.009)	(0.011)
(Precipitation)^2	-0.001***	-0.0001
	(0.0002)	(0.0002)
Temperature	0.070	0.095
	(0.076)	(0.058)
(Temperature)^2	-0.002	-0.002
	(0.002)	(0.002)
Holiday	6.713***	-4.513***
	(0.234)	(0.191)
Mean	56.5	71.43
User by Day of Week FE	Yes	Yes
Week-of-sample FE	Yes	Yes
Observations	1,346,392	1,335,638
R^2	0.432	0.325

Notes: This table contains results from estimation of modified Equation (1) for time spent at home on weekdays. Vacation days (as defined by the authors previously), including one day prior to vacating residence, have been excluded. The dependent variable is the percentage of time a user was home each day during the defined time windows. Number of half hour blocks the user was home divided by the observed number of half hour blocks times 100 gives the percentage of time a user was home. Standard errors are clustered at the census place level. *p<0.1; **p<0.05; ***p<0.01