Impact of Wildfire-induced Air Pollution on Time Allocation: Evidence from Smartphone Data

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January 15, 2025

Abstract

Wildfire-induced air pollution is contributing to a rollback in years of air quality gains in the United States. In this paper, we use novel mobility data with high spatial and temporal resolution to explore behavioral responses to air pollution shocks caused by wildfires in California. Using geo-localized cellphone pings, we construct individual, daily measures of time allocation. We estimate dose-response functions to wildfire-induced $PM_{2.5}$ air pollution for different time allocation metrics. Time spent at work, outside, and distance travelled decrease with pollution, while time at home and time spent inside increase. We observe some non-linearity in responses to extreme levels of pollution for time spent at home and inside. We explore heterogeneity in these responses across demographic groups and find suggestive evidence that Black and Hispanic residents adapt less than White and Asian residents to extreme levels of pollution. Estimating similar time allocation dose-response functions for precipitation, we find that the increase in time spent at home during an extreme pollution event is equivalent to approximately four times that of a rainy day. Finally, we seek to estimate the cost of these behavioral changes by comparing the change in time allocation caused by wildfire-induced pollution shocks to the change in time use caused by an increase in the price of retail gasoline.

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1 Introduction

Wildfire-induced air pollution is contributing to a rollback in years of air quality gains in the United States after decades of improvements (Clay, Muller, and Wang, 2021; Burke et al., 2022; Childs et al., 2022). Climate change is increasing the intensity and frequency of devastating fires and their associated toxic smoke plumes in the United States (Halofsky, Peterson, and Harvey (2020)). Strikingly, in recent years wildfire smoke has choked some of the largest population centers in the US with staggering pollution levels (see Figure 4). Wildfire smoke contains high concentrations of toxic pollutants, including fine particulate matter or $PM_{2.5}$. Exposure to wildfire smoke leads to a range of negative health outcomes, increasing ER visits, respiratory hospitalizations, and ultimately overall mortality (Gould et al., 2024; Reid et al., 2016; Cascio, 2018; Heaney et al., 2022).

Because of the well-documented negative impact of wildfire smoke on health, individuals try to mitigate their health risk by decreasing their exposure to wildfire smoke, and public information campaigns and pollution alerts likely also encourage these health-seeking behaviors. Indeed, public officials recommend people stay indoors during this type of event. We focus on this type of adaptation, and think of it as a behavioral response. The granularity of our mobility data makes this change in time use detectable (example: instead of going to the park, I stay home). Other important dimensions of adaptation, including defensive investments like masks, air-purifiers, and improved HVAC systems, are not the focus of this analysis. Even though spending more time indoors is among the simplest responses to wildfire-induced air pollution, evidence on this type of avoidance behavior is scant. This is partly due to challenges in obtaining a panel of time use and location choice with sufficient precision to detect changes triggered by wildfire smoke exposure. For instance, traditional data sources on time use, like the American Time Use Survey, are cross-sectional datasets based on small samples and limited in quality. These limitations make it nearly impossible to use these data to use precisely measure short-term changes in behavior in this data, such as the ones caused by the wildfire smoke.

We use a novel cellphone mobility dataset reporting individual, geolocated cell-phone pings for 120K devices to provide novel, precise estimates of individual time allocation. We observe on average 150 pings daily per device. Leveraging the exceptionally high spatial and temporal resolution of this dataset, we measure daily individual time use allocation for several time-use allocation metrics like time spent at home, work, inside, outside, and distance travelled. Compared to other time use datasets, we construct a panel with comprehensive measure of time allocation throughout the day without relying on surveys. This analysis focuses on California for the year 2018 because of data availability constraints and because 2018 was one of the state's worst fire seasons of all times (the Woolsey and Camp fires burnt in 2018, destroying the town of Paradise).

Leveraging this rich individual-level data, we provide insights into behavioral responses to wildfire-induced smoke by estimating pollution dose-response functions for several time-use allocation metrics, including time spent at home, inside, outside, and time at work. Our identification strategies rests on the plausibly exogenous occurrence and path of wildfire-induced smoke plumes. We find that time at home and time inside increase with pollution levels, and that the shape of the dose-

response function is slightly convex, showing a steeper response for extreme levels of pollution. Conversely, time spent outdoors, at work, and distance travelled decrease with pollution. We also perform a heterogeneity analysis by demographic groups and find suggestive evidence that for extreme levels of pollution, Blacks and Hispanics respond less than other groups, in line with other evidence that underprivileged are less able to adapt to weather shocks (Doremus, Jacqz, and Johnston, 2022). To benchmark these estimates, we also compute dose-response functions for precipitation. The increase in time spent at home on a day of extreme pollution (above 150 $\mu g/m^3$) is roughly four times that of the increase when there is a day of moderate rainfall. We also assess the change in time allocation caused by an increase in the $ per gallon price of retail gasoline and use this analysis to price the observed behavioral change caused by pollution shocks.

This paper adds to several streams of the literature. First, this work contributes to the novel literature using high-resolution mobility data to answer environmental questions (Lee and Beatty, 2025; Stechemesser and Wenz, 2023; Barwick et al., 2022; Long, Chen, and Rohla, 2020). We also build on the literature estimating the impact of weather shocks on time allocation to study similar responses but for pollution shocks (Zivin and Neidell, 2014a; Lee and Beatty, 20250). Also using cellphone mobility to compute time allocation changes, Lee and Beatty (2025) find significant changes in time allocation as a response to temperature shocks. On extreme-heat days, agricultural workers shift their work hours and work less on the first day of the temperature shock, but not necessarily on subsequent days.

This work also contributes to the literature highlighting the extent of pollution avoidance behavior. Using mobility data on high-speed rail, Barwick et al. (2022) find evidence of "haze-avoidance tourism": individuals use the high-speed rail system to travel towards clean-air destinations and therefore diminish their $PM_{2.5}$ exposure. More specifically, our analysis expands on the work of Neidell (2009) on avoidance behavior related to ozone pollution by using more precise and comprehensive data in the context of wildfire smoke. Neidell (2009) measures avoidance behavior by changes in time outdoor proxied by zoo and park attendance, which only provide a limited snapshot of outdoor time. In contrast, the spatial and temporal resolution of the individual cellphone mobility data makes it possible to comprehensively measure time spent outside and potential changes in outdoor activity.

Lastly, we also build on on the few existing papers specifically studying behavioral responses to wildfire smoke (Heft-Neal et al., 2023; Gellman, Walls, and Wibbenmeyer, 2024; Burke et al., 2022). Heft-Neal et al. (2023) find that the observed relationship between ER visits and smoke exposure suggests considerable avoidance behavior in the context of wildfire smoke exposure. At low levels of smoke exposure, California ER visits increase, but days with intense wildfire smoke exposure are associated with a decrease in ER visits, especially for injuries and non-urgent symptoms. The authors suggest that mediating behavior like staying home or indoors accounts for this reversal in ER visit trends. Our approach provides insights into the type of mediating behavior hinted at in the work of Heft-Neal et al. (2023). In the study that is closest to our approach, Burke et al. (2022) explore various behavioral responses to wildfire smoke events and find that during large wildfire-smoke events, google searches for air quality information and negative sentiment increase. Using

aggregate mobility data at the county-day level, Burke et al. (2022) also show that the proportion of individuals staying home the entire day increases during these fire events, particularly among the wealthy. In this paper, we deepen and expand this approach by constructing individual dose-response functions to wildfire-induced smoke for different time use metrics using individual, rather than aggregated, cell-phone mobility data.

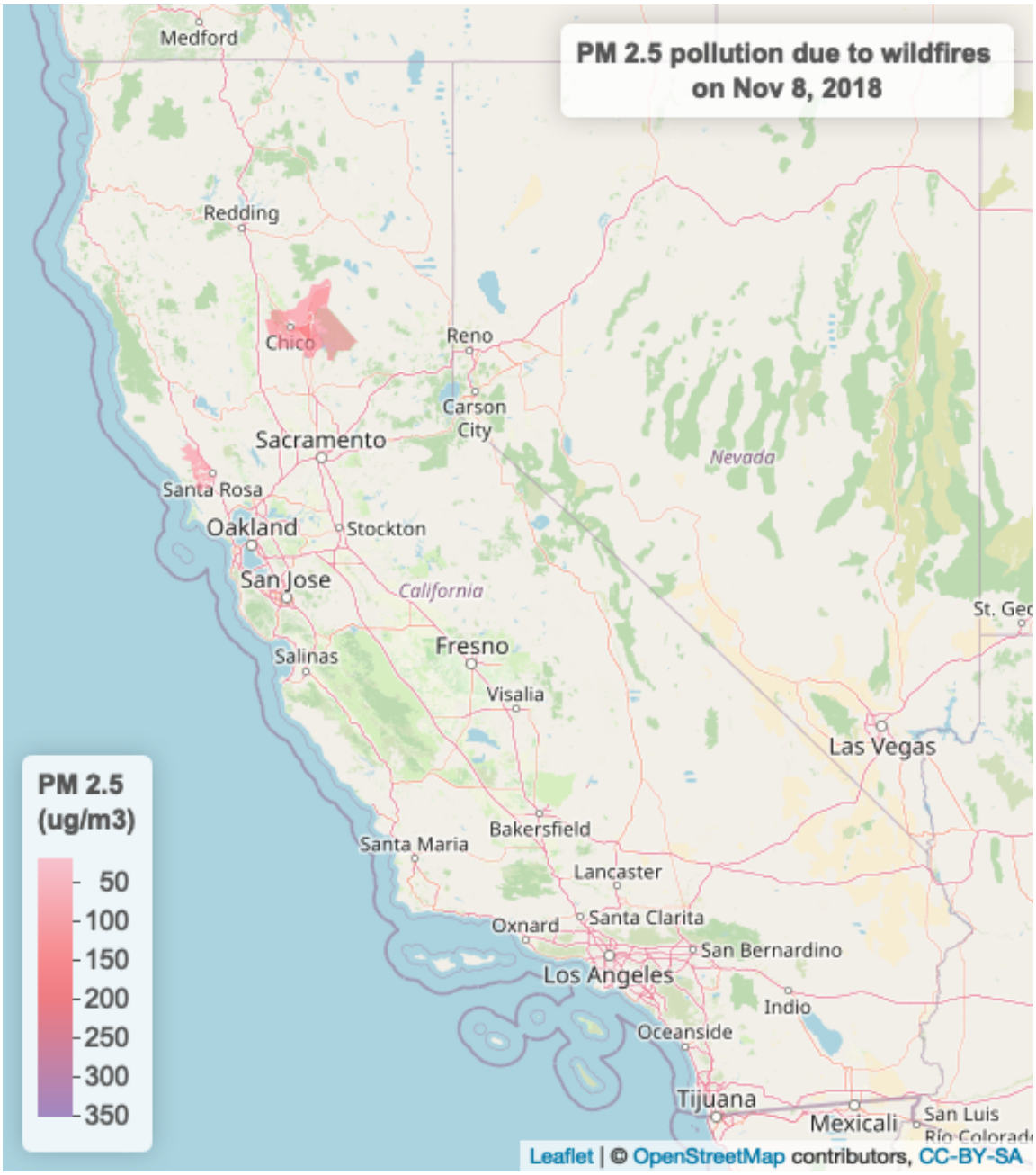
This paper is organized as follows. Section 2 details the data and methodology to construct time allocation metrics. Section 3 delves into the estimation strategy. Section 4 presents results and Section 5 presents pathways for future work.

2 Data and Methodology

2.1 Wilfire-induced $PM_{2.5}$ Metrics

To measure wildfire-induced pollution, we use the novel dataset produced by Childs et al. (2022), which we believe provides the most accurate available estimates of wildfire-induced $PM_{2.5}$ air pollution. This dataset uses a machine learning model to predict $PM_{2.5}$ concentration caused by wildfire at the daily level for the United-States. The resolution of the dataset is a 10x10 kilometer grid and spans the period 2006 to 2020. The machine learning model draws from differnece sources, including ground-truth measurements, remotely sensed and reanalysis products. Covariates include smoke trajectory, including ground-truth information from EPA monitors, meteorology, HISPLIT trajectories, fire variables, i.e. distance from the fire, aerosol measurements, predicted aerosol optical depth, and cross-sectional variables like elevation (Childs et al., 2022).

Figure 1: $PM_{2.5}$ Pollution generated by the Camp and Woolsey fires in California in November 2018 (Data: Childs et al. (2022). Author's own computation.)



For the overwhelming majority device-days observations in our sample, there is no wildfire-induced pollution (see table 1). Out of 18.7M device-day observations, wildfire-induced $PM_{2.5}$ pollution is between 0 and 25 $\mu g/m^3$ for 95% of observations, between 25 and 50 for 0.8%, 2.28 between 50 and 75 $\mu g/m^3$, .9% between 75 and 100 $\mu g/m^3$, and .63% above 100 $\mu g/m^3$ (see Figure 5 for the distribution of non-zero wildfire pollution days). Even though wildfire-induced air pollution remains a rare event in the sample, having almost 5% of device-day observations above 50 $\mu g/m^3$

is striking, given than the threshold for non-attainment PM 2.5 pollution used by the EPA sits at 35 $\mu g/m^3$. In the data, we observe wildfire-induced pollution from late June to November, which perfectly aligns with the typical duration and seasonality of California's fire season[1]. The 2018 Fire season was among the worst in the state's history, only surpassed by 2020 and 2021 in terms of surface burned. Before the 2025 Los Angeles fires, the 2018 fire season was the most destructive ($25 billion in damages and costs) and the deadliest fire season in California (103 fatalities)[2]. The Camp Fire alone, which destroyed the town of Paradise, caused the death of 85 people[3].

Early pollution spikes are tied to the Carr and Mendocino complex fire, which burned in Northern California in July and August 2018. These fires did generate toxic $PM_{2.5}$ air pollution, but pollution spikes over large population centers were curtailed to around 50 $\mu g/m^3$ (Cal Fire, 2021). In comparison, on top of being the deadliest and one of the most destructive fire in California's history, the Camp Fire generated some of the worst air pollution in California's history since monitoring began (see Figure 1 for an animation of the distribution of wildfire-induced pollution over California in November 2018).

2.2 Census, Temperature, and Rainfall data

We use data from the 2020 US Decennial Census to obtain information about the racial and ethnic composition of block groups. In a first step, we privilege studying inequalities along the racial and ethnic dimensions rather than other socioeconomic factors because of several factors. First, previous work has shown the importance of demographic inequalities in exposure to $PM_{2.5}$ (Daouda et al., 2022; Currie, Voorheis, and Walker, 2023). Second, Decennial Census Tables provide high-quality data at the blockgroup level, whereas data with the same granularity but for other socioeconomic dimensions like education or income would have to be pulled from the American Community Survey (ACS). The ACS at the blockgroup level is only available as 5-year averages and is based on relatively small samples, which can generate some issues with the precision of the provided estimates.

We use the PRISM gridded weather product with a fixed number of stations for daily minimum and maximum temperature and precipitation at the zip code level (Schlenker, 2024).

2.3 Mobility Data

We leverage smartphone ping data collected by Veraset (ex Safegraph) to construct time-use metrics. As explained in Atkin, Chen, and Popov (2022), phone operating system regularly record devices' geocoordinates. This information is shared with apps, when open or in background mode depending on user settings. During our period of interest, the ability of users to control the sharing of their location with apps was much lower and users had overall less agency over privacy settings (Android instituted the possibility to opt out of sharing location while apps were in background mode in 2019). Arguably, privacy concerns over this issue were not as much of an issue the public

[1] Guide to the California fire season from the Western Fire Chiefs Association.
[2] Source: Bloomberg, and NBC news
[3] Source: NBC news

debate. Companies like Veraset proceed to buy this information from different apps and aggregate the data. The dataset consists in anonymized, individual device identifiers, geocoordinates, timestamps, and a GPS margin of error generally amounting to a few meters. With this dataset, we have 120K devices for which we observe at least 10 pings daily and at least for 10 hours throughout the day.

This corresponds to about 1% of the adult California population between 18 and 75, that we observe between March 2018 to February 2019. We find that this sample is overall spatially representative, and that there do not appear to be strong patterns in overrepresentation of some Census tracts in the data (see example figure 6 for spatial distribution of devices as a percentage of Census Tract population within the Bay Area). However, the panel is unbalanced because data quality varies daily (i.e. one one day a device might ping 600 times, on another day for 15 hours, and on another it might not be present in the sample). In addition, some devices might drop off entirely from the sample. On average, we have high-quality data (more than 10 pings and 10 hours by day) for 97 days by device from March 2018 to February 2019. Concentrating on the fire season (July-December 2018), we observe an average of 58 high-quality data days by device.

This dataset with high spatiotemporal resolution has been used for various applications, including studying the spread of Covid-19 (Chen, Chevalier, and Long, 2021), knowledge spillovers (Atkin, Chen, and Popov, 2022), and church attendance (Pope, 2024). We believe that we are the first to use this dataset in its most granular form to study adaptation to air pollution, and among the first to apply it to environmental questions (Lee and Beatty, 2025; Long, Chen, and Rohla, 2020).

2.3.1 Methodology to construct time-use metrics

We leverage the richness of the cell phone ping dataset to construct daily time allocation at the individual level. We do not observe any characteristic at the individual level other than cell-phone pings. In this section, we explain our methodology to transform a sequence of discrete geo-localized pings with a timestamp into continuous metrics of time-use. As a first step, we identify the home location of a device as the modal location where the device pings at night during the third quarter of 2018. Similarly, we identify the workplace as the modal location where the device pings during weekdays during business hours. We are also able to identify whether the device is outside or inside by using a raster of buildings and determining whether each observed ping falls outside or inside of a building. This last measure is more subject to GPS error, because in this case the measure is sensitive to a couple meters, but we believe that GPS error is random enough that this does not affect our estimates as time use is an outcome variable. We compute daily distance travelled as the diagonal of the bounding box made up by the four pings which are the furthest apart during the day.

In the first step described above, we assign different categories to each ping: home ping, work ping, outside ping, inside ping. The second step consists in transforming this discrete list of pings into a continuous measure of time use. To make this transition, we need to make some inference about what happens between two pings. First, we consider that a device is travelling if the elapsed time and distance between two pings leeds to a speed above 10km/hour. The first assumption is a

non-parametric one. Consider that a device is not travelling and is observed at time x at location i and a ping at time $x+1$ at location j. We consider that this elapsed time is split evenly between i and j if the device is not travelling. For instance, on figure 7, this assumption means that for the one hour elapsed between ping 4 at home and ping 5 at work, we assign 30 minutes to home and 30 minutes to work. We also make a couple of parametric assumptions. For instance, if the first ping of the day is before 9AM in the home, we consider that the period between midnight and the first ping are spent at home. Similarly, if the last ping of the day is after 8PM within the home, we consider that the time remaining between the last ping and midnight is also spent in the home. We also assume that time spent in the office is a single interval. This means that we compute time spent in the office as time elapsed between the first ping of the day in the office and last ping of the day in the day in the office. That is, if the person goes out for lunch during her workday or attends a meeting in a different building, this will still be considered work time. Importantly, we do not *constrain* any of the time-use metrics: we do not impose that the number of observed hours on a given day sums up to 24. Therefore, on a given day, the number of hours observed can vary by device, and as a result for some device-day observations included in the sample we only partially observe time-use throughout the day, as exposed in Figure 7 example 3.

2.3.2 Descriptive Statistics

Applying this methodology, we obtain estimates of time allocation at the device-day level. We find that for devices reporting more than 10 pings a day amounting to more than 10 hours during the day, the average daily time spent at home is 11 hours, the average hours spent at work 7, hours inside 14, and hours outside 4 (see Figure 8 for descriptive statistics). We benchmark our estimates with geocoded data from the American Time Use Survey (ATUS) for California over the years 2010-2022 compiled by Gibson and Shrader (2018) The ATUS is a cross-sectional survey where participants are asked to keep a diary of all their activities over a 24 hour period. We find that our average estimates of time use match ATUS, except for time spent outside. On average, ATUS reports that adults spend 10.5 hours at home, spend on average 7 hours at work, and 40 minutes outside. The large discrepancy for time spent outside most likely reflects challenges in using ATUS to recreate this metric as well as an overestimation of time spent outside in our data[4]. Since the ATUS is activity focused (example question: how much time did you spend doing house chores today?), it does not directly ask the proportion of time spent outside versus inside. Following Zivin and Neidell (2014b), we assign whether each activity recorded by ATUS can be done outside or inside, but this remains an imperfect approach. The response rates for activities potentially done outside such as sports is very low. Compared to ATUS, we create a dataset focused on changes in time spent outside and inside with the major advantage of having an individual panel structure.

[4]this should not affect our estimates as long as variation in time use is correctly captured and measurement error is random.

3 Identification Strategy

We aim to estimate dose-response functions to wildfire-induced air pollution. The goal of this first step is to causally estimate the behavioral responses to wildfire-induced pollution events. The "treatment" here is exposure to wildfire pollution, and it is continuous. The identifying assumption is that air pollution generated by wildfires constitutes an exogenous pollution shock. Other point sources of $PM_{2.5}$ pollution like fossil fuel combustion are more likely to covary with economic activity or be determined by endogenous sorting within urban centers and therefore cannot be considered exogenous. Large wildfires, like the 2018 California wildfires, generate enormous smoke plumes made up of particulate matter and other pollutants, like carbon oxide and other volatile compounds, that are released during the combustion. As explained in Borgschulte, Molitor, and Zou (2022), these smoke plumes can travel thousands of miles and their direction is determined by wind, meteorology, and topography, parameters that are a priori independent of any human behavior. Because of variability in wind patterns and fire dynamics, the direction and intensity of a smoke plume is very difficult to predict. Usually, the smoke plume and its associated pollution linger for a few days, but the length of the shock is also difficult to predict and dependent on fire and atmospheric characteristics. Smoke plumes cover extensive areas, and within a geographic area like a city, variation in exposure to a shock such as a smoke plume is minimal. Importantly, the smoke plume can therefore be considered a blanket shock across one urban area. Therefore, the variation in pollution at the scale of work-home commute should be minimal. We believe that this enables us to proxy the exposure of an individual by using the $PM_{2.5}$ concentration assigned to its home location without too much error.

We expect responses to be heterogenous according to the pollution level. Our expectation is that responses will intensify with the strength of treatment, i.e. the worst the pollution the larger the response. To capture heterogeneity in responses, we run a binned specification allowing the response to differ by levels of pollution. We expect the dose-response function to reflect adaptation mechanisms through different channels. First, as the pollution becomes more salient, individuals might physiologically feel that the air is deteriorating and seek protection. Second, as pollution becomes more salient, individuals might become aware of the pollution visually by noticing the haze created by the smoke plume. Fourth, as pollution levels increase, news coverage about the smoke plume might also increase. Pollution alerts might also be issued, leading individuals to seek shelter. Last, and this is not an adaptation channel, individuals might become sick from the pollution and become unable to leave their home.

We estimate the following equation:

$$y_{it} = \alpha + \sum_{k} \beta_k bin PM_{skt} + \mathbf{X_{it}} + \omega_i + \omega_m + \omega_{dow} + \epsilon_i \tag{1}$$

The outcome y_{it} is one of the time-use metrics of interest, which varies daily t at the device i level. We construct 7 bins of wildfire-induced $PM_{2.5}$ in increments of 25 $\mu g/m^3$. The 0-25 $\mu g/m^3$ bin is the reference category and the last bin includes all device-day observations where the pollution level

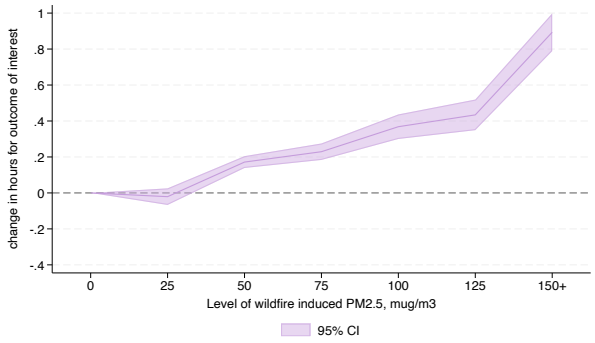
is above 150 $\mu g/m^3$. As discussed previously, the $PM_{2.5}$ device exposure level is assigned based on the home location of the device at the tract level s. Temperature and pollution are likely to impact time-allocation and pollution non-linearly, so quadratics in average temperature and precipitation are also included as controls. The specification includes different fixed effects. Device fixed effects ω_i capture differences in time-use patterns among devices. Month fixed effects ω_m account for different time use patterns across different seasons. Time allocation is likely to vary across seasons because of weather and travelling patterns. Day-of-the-week fixed effects control for different time use patterns across weekdays. This may be particularly important because time allocation is very different between days off and days at work (i.e mostly week-ends and week-days).

4 Results

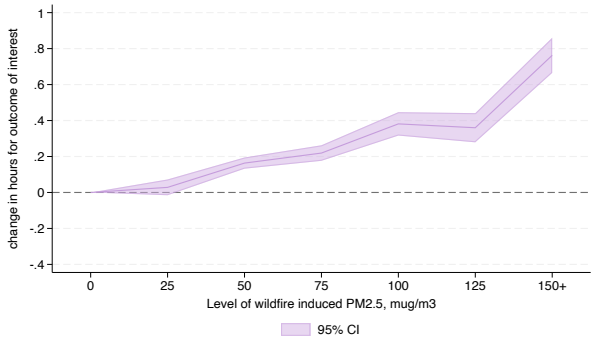
4.1 Dose-response functions

Figure 2: Wildfire Smoke and Behavioral Change. Bins are from 0 $\mu g/m^3$ of $PM_{2.5}$ pollution to $150\mu g/m^3$ and above, in 25 $\mu g/m^3$ increments. The first bin is the reference category. Controls for quadratics in temperature and precipitation, and month, day-of-week, and device fixed effects. For reference, the EPA non-conformity standards is 35 $\mu g/m^3$.

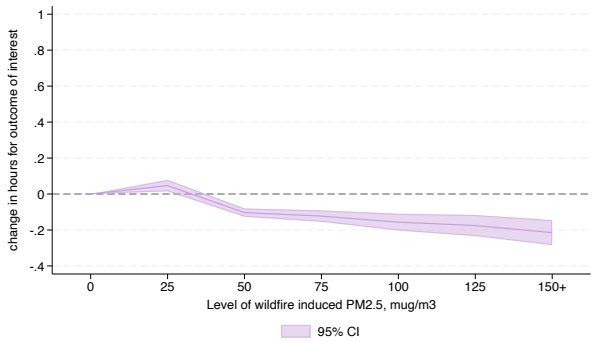
(a) Hours At Home



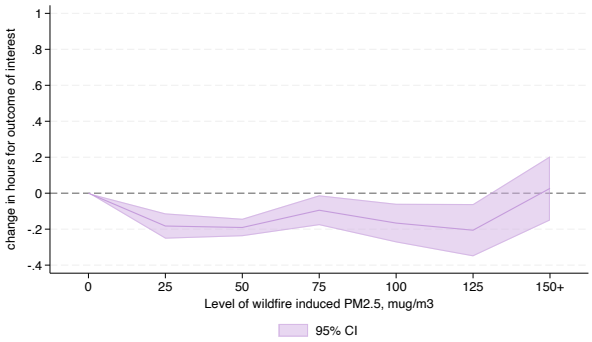
(b) Hours Inside



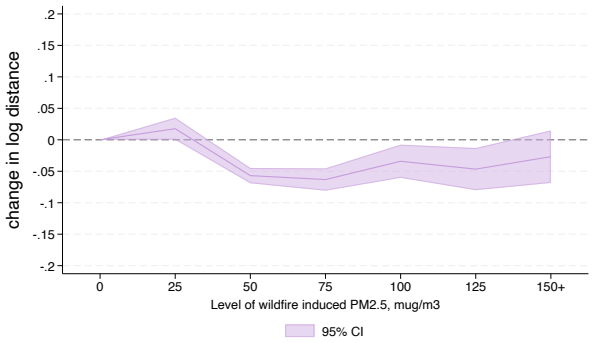
(c) Hours Outside



(d) Hours At Work



(e) Log Max Distance



We find that time use responds to wildfire smoke exposure, providing evidence of avoidance behavior in the form of changes in time allocation. Dose-response functions to pollution for several measures of time-use metrics are shown in Figure 2 and corresponding estimates are reported in table 2.

When faced with a pollution shock, we find that individuals spend more time at home, more time inside, less time outside, less time at work, and decrease their distance travelled. For time spent at home and time spent inside, we observe slightly convex dose-response functions, indicating an increasing response with the level of pollution. Compared to days with pollution levels between 0 and 25 $\mu g/m^3$ (low pollution days), individuals spend on average 54 more minutes at home when wildfire smoke induces $PM_{2.5}$ pollution above 150 $\mu g/m^3$, and 25 more minutes at home when $PM_{2.5}$ is between 50 and 100 $\mu g/m^3$. Similarly, individuals spend an additional 48 minutes at home on days with pollution concentrations above 150 $\mu g/m^3$ compared to low pollution days. The slightly smaller magnitude of the response for time spent inside compared to time spent at home could indicate switching behavior. Overall time spent inside may increase less than time spent at home if, for instance, individuals trade time spent dining out with time spent in the home. We observe a decrease in time spent outside of 13 minutes for pollution days above 150 $\mu g/m^3$. The lack of symetry between the estimated change in time spent outside and time spent inside could be driven by the structure of the data since we do not require to observe 24 hours of data daily for each device. Furthermore, we separately estimate equation 1 for time outside and time inside, refraining from constraining coefficients to sum to zero. In addition, in all the empirical analysis, the sample is restricted to "high-quality" data, that is observing at least 10 hours of data and 10 pings for that device on a given day.

We also find that as pollution increases time spent at work decreases by 5 to 13 minutes depending on the level of pollution (see Table 2). The magnitude of this effect seems to be in line with the estimates of Hoffmann and Rud (2024) on the impact of pollution on hours worked in Mexico City. Since workplace identification is only possible for a subset of the sample, sample size diminishes considerably when computing the response of working hours to smoke. Our methodology to identify the workplace is based on identifying regular visits to a building during business hours. We are therefore only able to identify office workers, leaving out for instance gig workers, who might have both a more flexible labor supply and a higher probability of working outside and of being exposed to smoke. This sample restriction combined with the low frequency of extreme pollution days could account for the imprecision of the estimated coefficient for the impact of smoke days above 150 $\mu g/m^3$ on worked hours in Table 2 column 4. Interestingly, and bearing in mind the previously mentionned caveats, the dose response function for hours at work is roughly constant, rather than decreasing with pollution levels. We interpret this result as potentially being driven by labor supply inelasticity. Compared to their time spent at home and time spent outside, office workers probably only have limied flexibility in their work supply. Taken altogether, these results could suggest that individuals adapt to wildfire smoke by adjusting more along the leisure dimension, here outdoor activities, than along the work dimension.

Last, we also find that distance travelled decreases by 5.8 to 6.5% for levels of pollution above 50

$\mu g/m^3$[5]. This overall decrease in distance travelled as pollution increases is coherent with increased time spent at home and inside. All in all, these results document that wildfire smoke induces large behavioral responses in the form of changes in time allocation.

4.2 Robustness Checks

Our results on the impact of smoke on time allocation are robust to several alternative specifications. First, as an alternative to the binned model, we also estimate a cubic spline model in order to better capture non-linearities in the behavioral response to pollution (see Figure 9). The cubic spline and binned specification yield similar estimates, but using the cubic spline model indicates that the response to high levels of pollutions is steeper and more convex for hours spent at home than for time spent outside.

The general direction of the effect does not depend on the chosen structure of fixed effects (see table 3). Without any fixed effects, the magnitude of the effect for hours spent at home is larger, with 1.5 hours spent at home on a day with 150 $\mu g/m^3$ compared to 54 minutes for our baseline estimates. Expectly, we note that month-fixed effects absorb some of the variation, most likely because of seasonal patterns in time spent at home, which are also tied to overall weather. Similarly, device fixed-effects account for some of the variation in time spent at home, reflecting heterogeneity in the amount of time spent home by individuals, and most likely also heterogeneity in cell-phone pinging patterns reflecting different individual app use. We also note the importance of day-of-week fixed effects since time spent at home varies considerably between weekdays and weekends, and omitting this control masks part of the effect, in part because some of days with the largest pollution in our sample, in November 2018, fall on weekends.

To allow for more flexibility in seasonality, we also run a specification including a cubic time trend instead of monthly fixed effects. Results are very similar to the baseline specification (see table 5). The results are also robust to clustering of the standard errors at the treatment level, which is roughly at the day $\times$ zip-code level. Expectedly, clustering at the day $\times$ zip-code level does increase standard errors two- or threefold but coefficients remain statistically significant at conventional levels (see table 4).

4.3 Heterogeneous Responses By Demographic Groups

We explore whether the response to pollution shocks varies by demographic groups (see Figure 10). A growing body of work documents that underprivileged racial and socioeconomic groups are overexposed to environmental risks like extreme heat and air pollution ((Daouda et al., 2022; Currie, Voorheis, and Walker, 2023; Brazil, 2022; Stechemesser and Wenz, 2023)). Recent work also suggests that climate change might exacerbate these inequalities (Doremus, Jacqz, and Johnston, 2022; Papp, 2024). In the context of wildfire-induced air pollution, Burke et al. (2022) establish that richer populations are more likely to search for information on air filters, are more likely to feel negatively about the wildfire, and are more likely to not leave their home on that day. Thanks to the

[5] in column 5 in table 2, the outcome distance travelled in logged, so to interpret the coefficient we compute $\exp(\beta) - 1$.

granularity of our mobility data, we can compute dose-response functions by demographic groups for different time-use allocations. We infer the plausible demographic group of a device based on the home location of that device and its associated block demographic composition recorded in the 2020 Decennial Census. A Census blockgroup consists in a couple hundred residents and is the second smallest unit in the US Census. Proxying race or ethnicity based on this information seems a good approximation, at least in cities, because of the degree of segregation of US cities (Lichter, Thiede, and Brooks, 2023). We use a weighted approach to construct differential dose-response functions by demographic groups. For each category, we weigh the baseline regression equation according to the respective weight of that blockgroup with respect to that category. For instance, consider that $x_{h,i}$ represents the number of Hispanics living in blockgroup i. The weight of that blockgroup will be $\frac{x_{h,i}}{Pop_h}$ where $Pop_h = \sum_i x_{i,h}$ is the total Hispanic population in our sample. We also use an alternative cut-off approach where we compute a category's dose response function by only keeping the top 20% blocks which have the highest share of that category (see Figure 11). The two approaches yield very similar results.

We do not observe differences in responses across groups for high but not extreme levels of pollution (below 100 $\mu g/m^3$), but there does seem to be differences in responses for pollution concentrations above that level. In that case, underprivileged socioeconomic groups seem to respond *less* to extreme $PM_{2.5}$ concentrations than other groups (see Figure 10). Our findings suggest that Hispanic and Black residents adapt to a lesser extent than their White and Asian counterparts, which would be in line with other findings in the literature on adaptation inequalities (Doremus, Jacqz, and Johnston, 2022; Burke et al., 2022). However, there are some caveats to that interpretation. First, the weighting or cutoff approaches are combined with a much smaller number of observations for days with extreme pollution, and there could be power concerns here. For some pairwise comparisons, confidence intervals between point estimates overlap and are not statistically different from each other. However, if we give weight to this suggestive evidence, these results highlight a new dimension of adaptation inequality.

4.4 Benchmarking Results with Dose-Responses to Precipitation

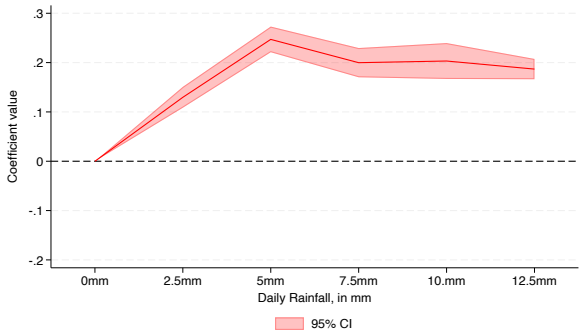
We compute dose-response functions to precipitation for time allocation to benchmark responses to pollution with other environmental shocks. Because utility gains from rain for agriculture or increased water supply are mostly long-term, we make the assumption that, in the very short-term, individual utility is decreasing both in pollution and precipitation. To this extent, pollution and rain could be considered similar types of shocks. It would for instance be more difficult to use temperature as a comparator, as individual short-term utility *increases* with temperature until a certain temperature threshold. However, this comparison has many limits. Rain itself does not present a risk for human health, whereas pollution does. Rather, health risks come from the consequence of torrential rain like flooding or landslides. Rain also increases the likelihood of accidents, which might not necessarily be true for pollution. Despite these limitations, we believe that benchmarking our estimates with behavioral responses to rainfall is valuable. At the very least, this exercise provides a useful validation step. Rain is a much more frequent environmental event than extreme wildfire-induced pollution shocks, and behavioral responses to rain are therefore

better understood. In that dimenstion, this rainfall analysis also represents an additional check concerning the quality of our data and time use metrics and of their ability to detect short term behavioral changes as a response to environmental shocks.

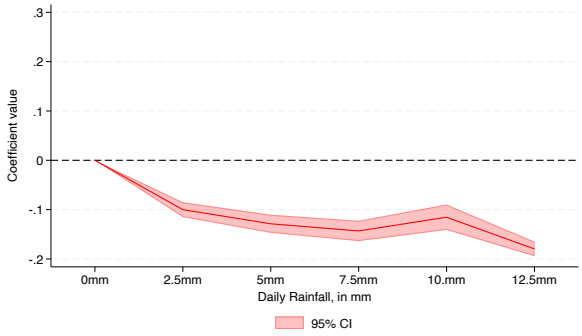
We estimate a similar binned specification than for our baseline estimates as described in equation 1, but using bins of precipitation as covariates, and controlling for wildfire-induced pollution. We use precipitation bins of 2.5 millimeters (mm) from 0 to 12.5mm and above. A day with 12.5 mm corresponds to a day with moderate rainfall. Because the study region is California, the distribution of rainfall is extremely skewed to the left, and on most device-days observations rainfall is zero, with very few data points with heavy rainfall (in that sense, the precipitation distribution resembles the distribution of wildfire-induced pollution, see Figure 12). Consistent with expectations, we find that on rainy days, individuals spend more time at home and inside, less time outside, and decrease their distance travelled. Estimating precipitation dose-response functions for different time allocation metrics, we find that when it rains more than 5mm in a day, time at home and time inside increase by roughly 12 minutes while time outside decreases by roughly the same amount (see Figure 3). We see no effect of time at work except a very small effect for days where precipitation is above 12.5mm. In terms of magnitude, the behavioral response for hours spent at home and inside is about 4 times larger for a pollution shock larger than 150 $\mu g/m^3$ than for a day with total precipitation above 12.5 mm. The response in terms of hours spent outside is of the same magnitude. Distance travelled decreases more as a response to days with large rainfall than for a day with extreme pollution (18% decrease for days with above 12.5mm precipitation versus a 6% decrease for a day above 150 $\mu g/m^3$). A potential explanation is that in the case of wildfires, a few individuals in the sample may have to evacuate or flee the smoke plume, therefore increasing distance travelled.

Figure 3: Behavioral Responses to Precipitation. Bins from 0 to 12.5+MM of precipitation. The first bin is the reference category. Controls for pollution and for temperature, month, day-of-week, and device fixed effects.

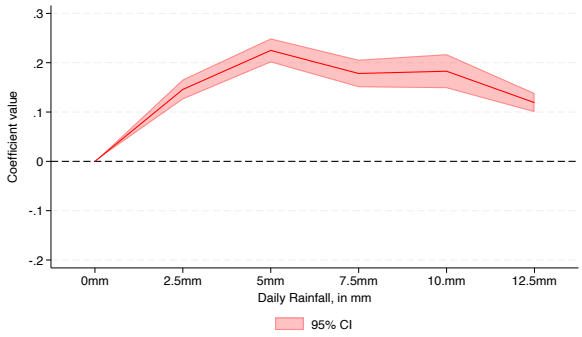
(a) Hours At Home



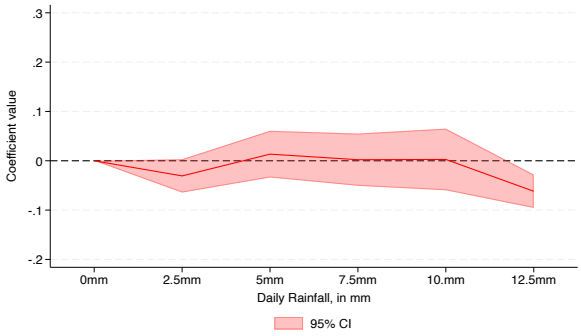
(b) Hours Outside



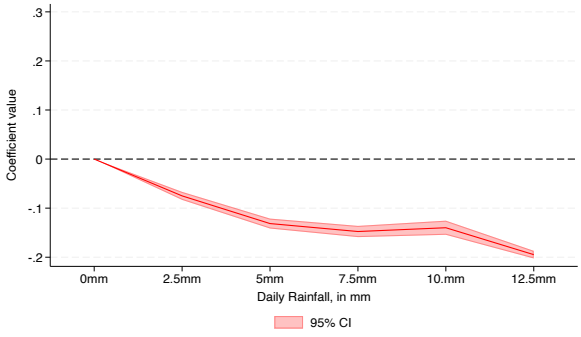
(c) Hours Inside



(d) Hours At Work



(e) Log Max Distance



4.5 Quantifying the Cost of Time Switching Using Gas Prices

In this section, we seek to assess the cost of this observed behavioral change. We aim to estimates non-health costs associated with pollution shocks by comparing changes in behavior caused by changes in pollution to changes in behavior caused by changes in gas prices. One of the challenges associated with valuing costs associated with time allocation changes is that observed changes consist in time switching, rather than time strictly lost. For example, the observed increase in time

spent at home could indicate a transformation from time spent outside, at work, or at other indoor leisure locations, into time spent at home. That time spent at home does not have a value of zero, but presumably there is a utility loss from switching compared to other activities.

We explore the possibility of using gas prices to benchmark the change in behavior during pollution shocks. A large body of work documents an important consumer elasticity to changes in retail gasoline prices (Puller and Greening, 1999; Hastings and Shapiro, 2013). Among many other impacts, we posit that changes in gas prices induce behavioral changes akin to time switching, and that they are potentially similar to the effect of pollution shocks in that specific dimension. For instance, an increase in the gas price might lead consumers to forgo certain trips and prefer staying home, a mechanism that we also observe for wildfire-induced pollution shocks.

We run a simple, first stage regression to establish the impact of changes in retail gasoline prices on our different time allocation metrics (see table 7). Figure 14 indicates that there is some variation in the price of retail gasoline in the period of interests, as retail gasoline prices decreased between October 2018 and March 2019 by approximately 0.5 $ per gallon. We aggregate time use estimates at the weekly level to match retail gasoline price data for California available from the Energy Information Administration (EIA). We find that hours at home and hours inside increase with retail gasoline prices while hours outside and distance travelled decrease (see table 7). We use the coefficients from this regression to back out the equivalent of a day above 150 $\mu g/m^3$ in terms of a dollar per gallon increase in the retail gas price. For hours at home, we find that a 1$ increase in the price of retail gasoline leads to on average 1.3 additional hours at home. Considering that a day above $150\mu g/m^3$ leads to 0.893 additional hours at home, this entails that the behavioral response for a day above 150 $\mu g/m^3$ is equivalent to that of a 0.68 $/gallon increase in the $ per gallon increase in the price of retail gasoline, which amounts to a large shock (see Figure 14). Performing the same exercise but with different time allocation outcomes, we find that a day at $150\mu g/m^3$ is equivalent on average to a .19 to .83 $ per gallon increase in the price of gasoline.

5 Conclusions and Pathways For Future Work

This paper explores behavioral responses to wildfire smoke using cellphone mobility data. Our first contribution is the creation of a novel panel dataset reconstructing individual time-use from cell-phone mobility data with high spatio-temporal resolution. We then use this dataset to compute dose-response functions to wildfire-induced air pollution for different time allocation metrics. We observe that individuals do respond to wildfire smoke by spending more time inside and at home, and by decreasing their time spent outside, hours worked, and their distance travelled. We observe that these for time spent at home, inside, and outside, these responses are larger for higher levels of pollution. We also document heteregoneous responses across demographic groups and benchmark the size of this response with responses to precipitation. To the best of our knowledge, this study is the first to estimate short-term individual behavioral responses to wildfire smoke shocks. We therefore believe that this work provides important information for researchers and policymakers as California and the Western United States face increasing wildfire risks due to climate change.

We also explore the cost associated with this observed behavioral change by using gas prices, an approach that we hope to develop more in further work. An obvious limitation of the current analysis is that it is unclear that changes in retail gasoline prices are exogenous, as they might be correlated with the broader economic context. To address this issue, in future steps we plan to instrument gas prices in California with gas prices from other states. Increases in retail gasoline prices also introduces other types of consumption switching that are not captured by time switching. In addition, the nature of the two shocks are extremely different and this also potentially limits the interest of this exercise. However, this approach has the advantage of providing a monetary estimate for time switching, using a mechanism plausibly similar to the behavioral change induced by wildfire-induced pollution.

We are also working to extend our analysis to work on intertemporal substitution dynamics. One advantage of this dataset over other sources of data is the ability to repeatedly observe the same individual at a high frequency over time, and therefore map very precise behavioral changes from one day to the next. Beyond the precision and sampling advantage of using mobility data to reconstruct time use, obtaining panel data for time use is even rarer. Our dataset makes it possible to explore the exact duration of the pollution shock and potentially quantify whether there are intertemporal substitution mechanisms at play. To start this work, we use an event-study framework around the Camp Fire in November 2018 in the Bay Area (see Figure 13) considering time spent at home as an outcome. According to this graph, time at home responds most when the pollution shock occurs on a weekday. We potentially observe large intertemporal substitution effects. As soon as the pollution subsides, individuals compensate time not spent at home with time spent outside the home. The compensation seems to be of the same order of magnitude. In the future, we plan to extend this analysis to other time-use metrics and other pollution shocks to better quantify the magnitude of the compensation.

Figures

Figure 4: Bay Area $PM_{2.5}$ pollution since 2006. Own computation, but reflecting this twitter post by Marshall Burke. Data from Childs et al. (2022) As a reference 35 $\mu g/m^3$ is the threshold value for non-attainment set by the EPA.

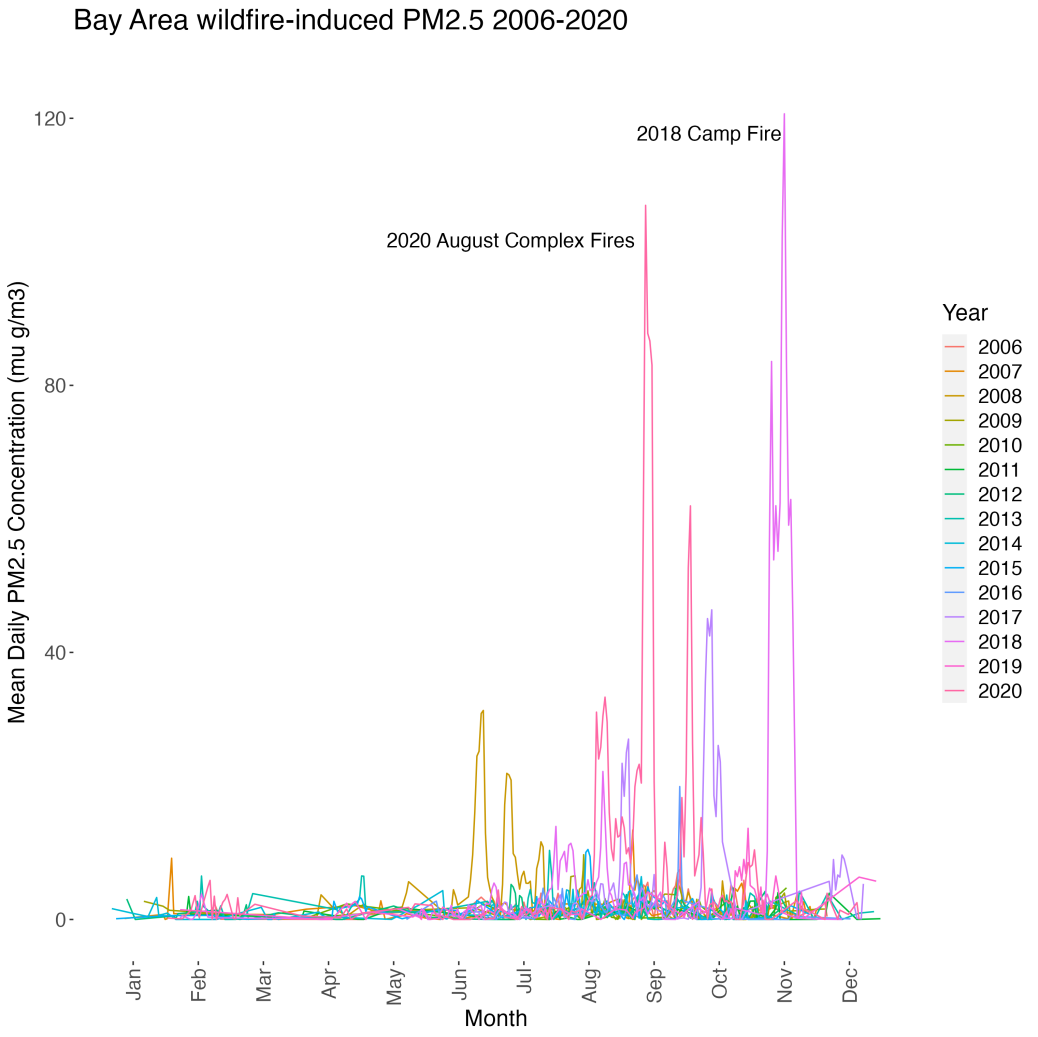


Figure 5: Distribution of non-zero wildfire-induced pollution device-days

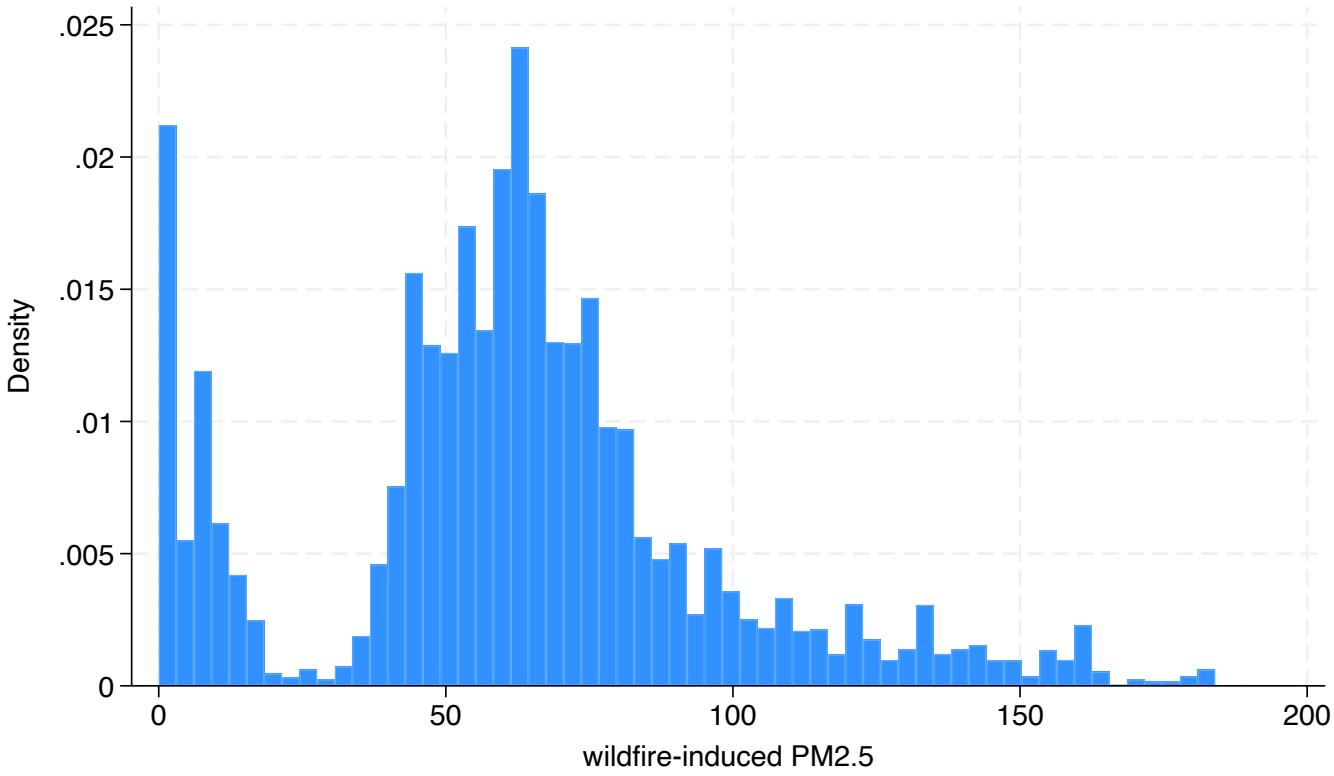


Figure 6: Representativity of the Cell-Phone data in the Bay Area

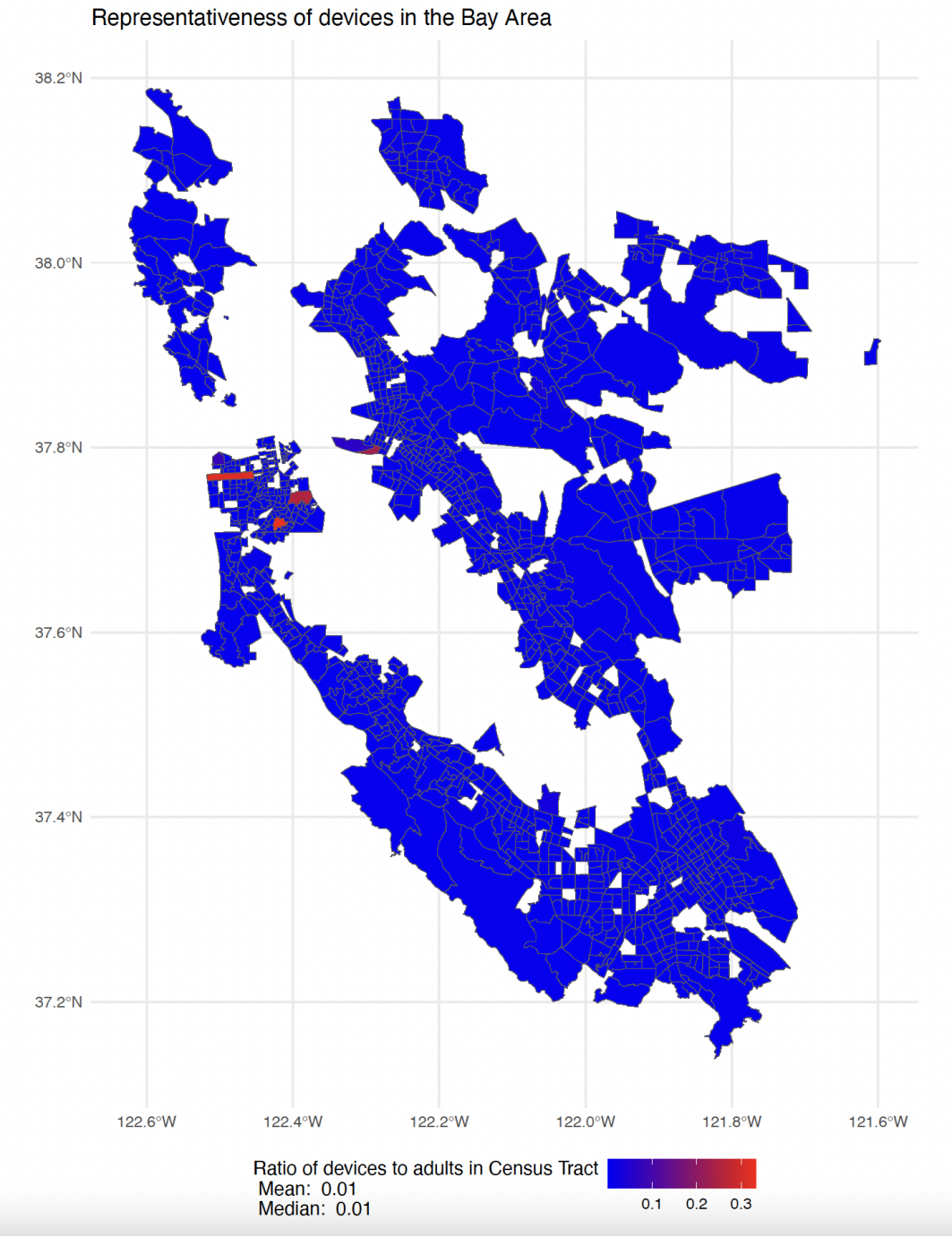


Figure 7: Examples of Methodology

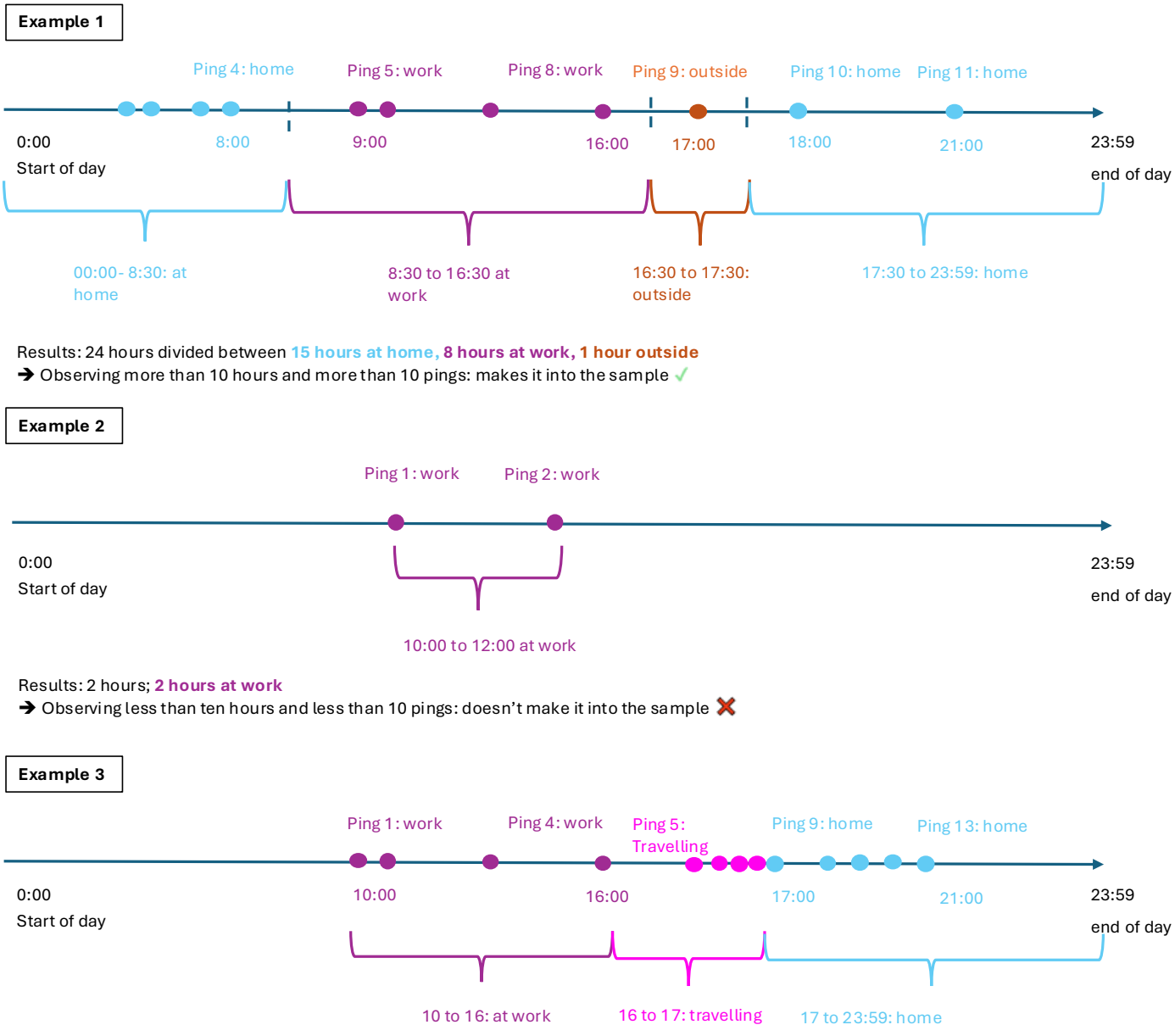
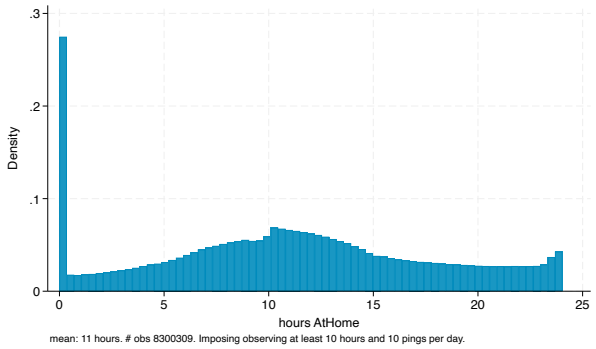


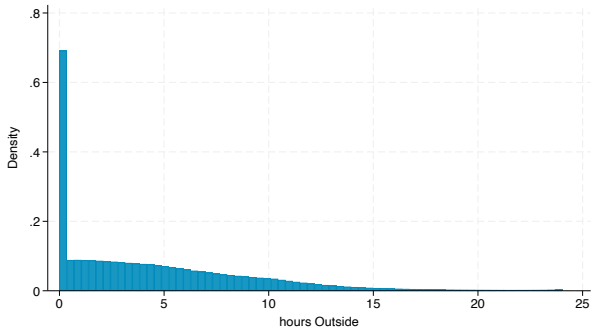
Figure 8: Descriptive Statistics for constructed metrics of time-use

(a) Hours At Home



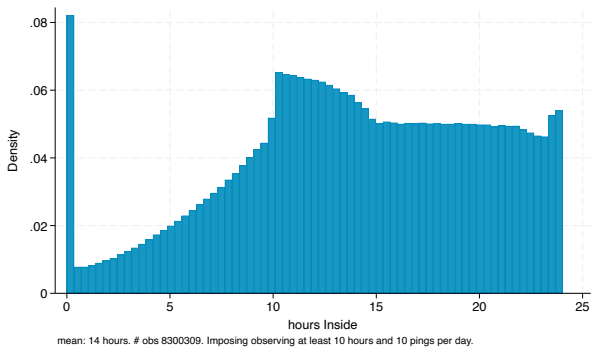
mean: 11 hours. # obs 8300309. Imposing observing at least 10 hours and 10 pings per day.

(b) Hours Outside



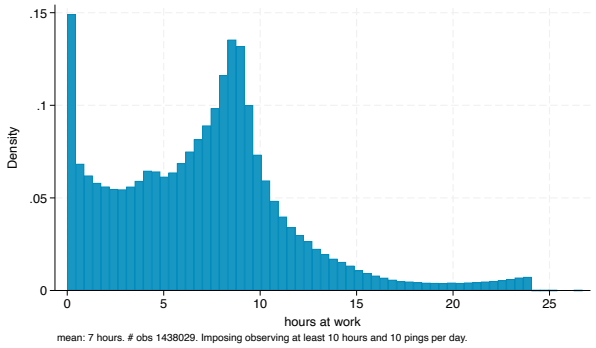
mean: 4 hours. # obs 8300309. Imposing observing at least 10 hours and 10 pings per day.

(c) Hours Inside



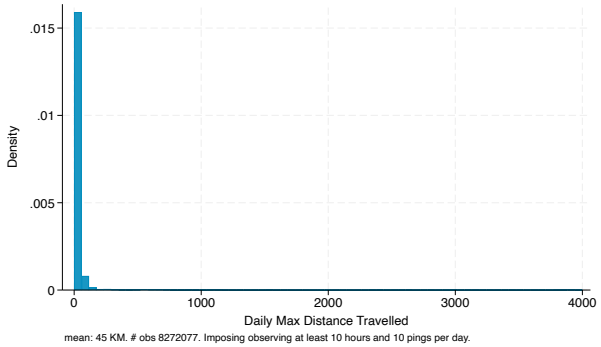
mean: 14 hours. # obs 8300309. Imposing observing at least 10 hours and 10 pings per day.

(d) Hours At Work



mean: 7 hours. # obs 1438029. Imposing observing at least 10 hours and 10 pings per day.

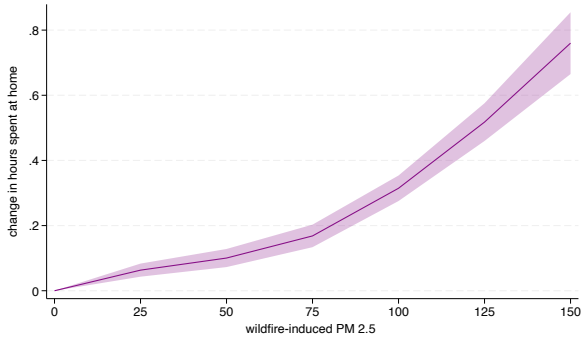
(e) Max Distance



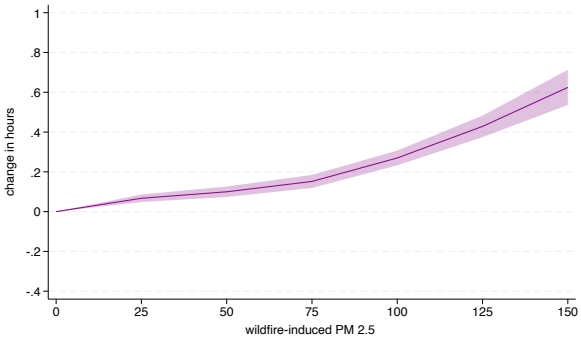
mean: 45 KM. # obs 8272077. Imposing observing at least 10 hours and 10 pings per day.

Figure 9: Wildfire Smoke and Behavioral Change, using a cubic spline specification. Bins 0 $\mu g/m^3$ of $PM_{2.5}$ pollution to 150 and above in 25 $\mu g/m^3$ increments. The first bin is the reference category. Controls for pollution and for temperature, month, day-of-week, and device fixed effects. The EPA non-conformity standards sits at 35 mug/m3

(a) Hours At Home



(b) Hours Inside



(c) Hours Outside

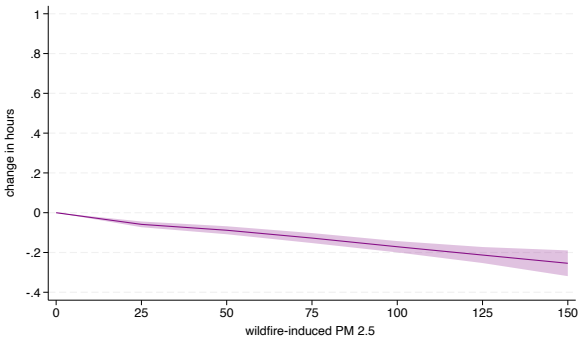


Figure 10: Heterogeneous Response to Wildfire-Induced Pollution by Demographic Group. Outcome variable: Hours At Home. Y-axis: change in hours spent at home following a pollution shock. Weighting approach.

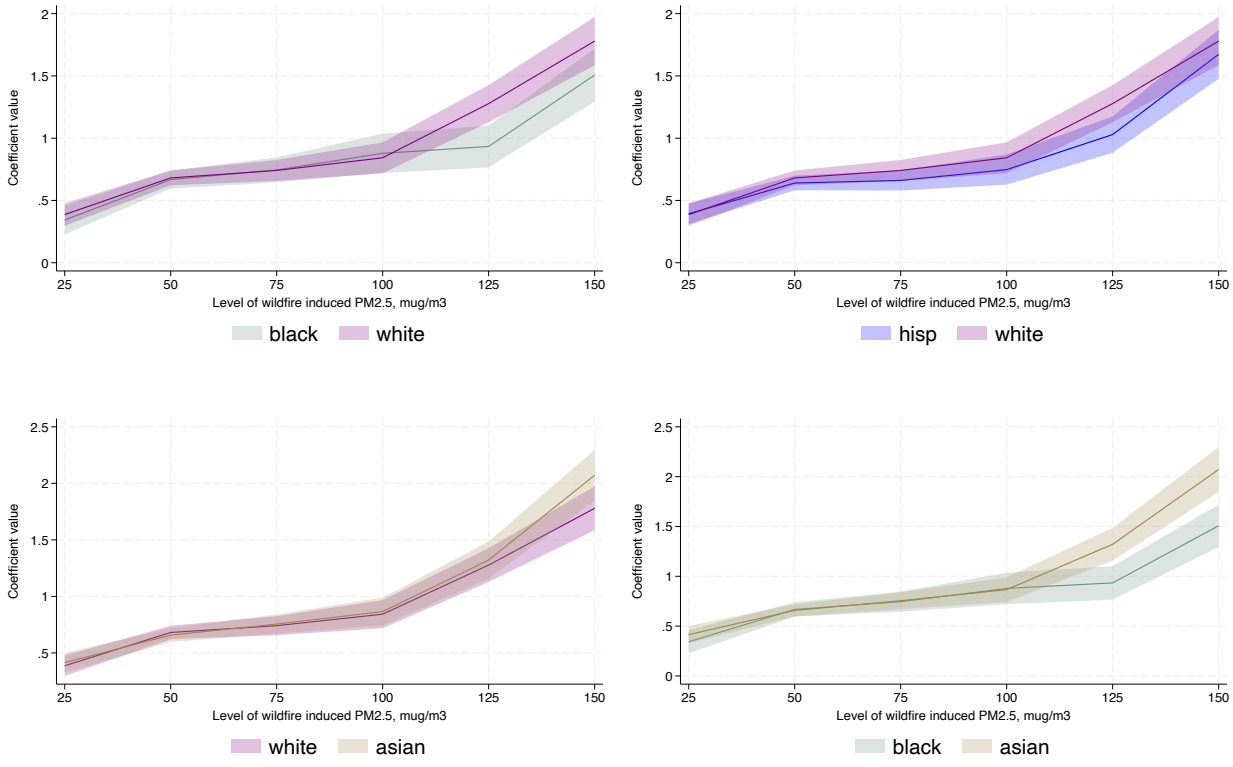


Figure 11: Heterogeneous Response to Wildfire-Induced Pollution by Demographic Group. Outcome variable: Hours At Home. Y-axis: change in hours spent at home following a pollution shock. **Cut-off** approach, i.e only keeping the top 20% blockgroups with the highest share of that category.

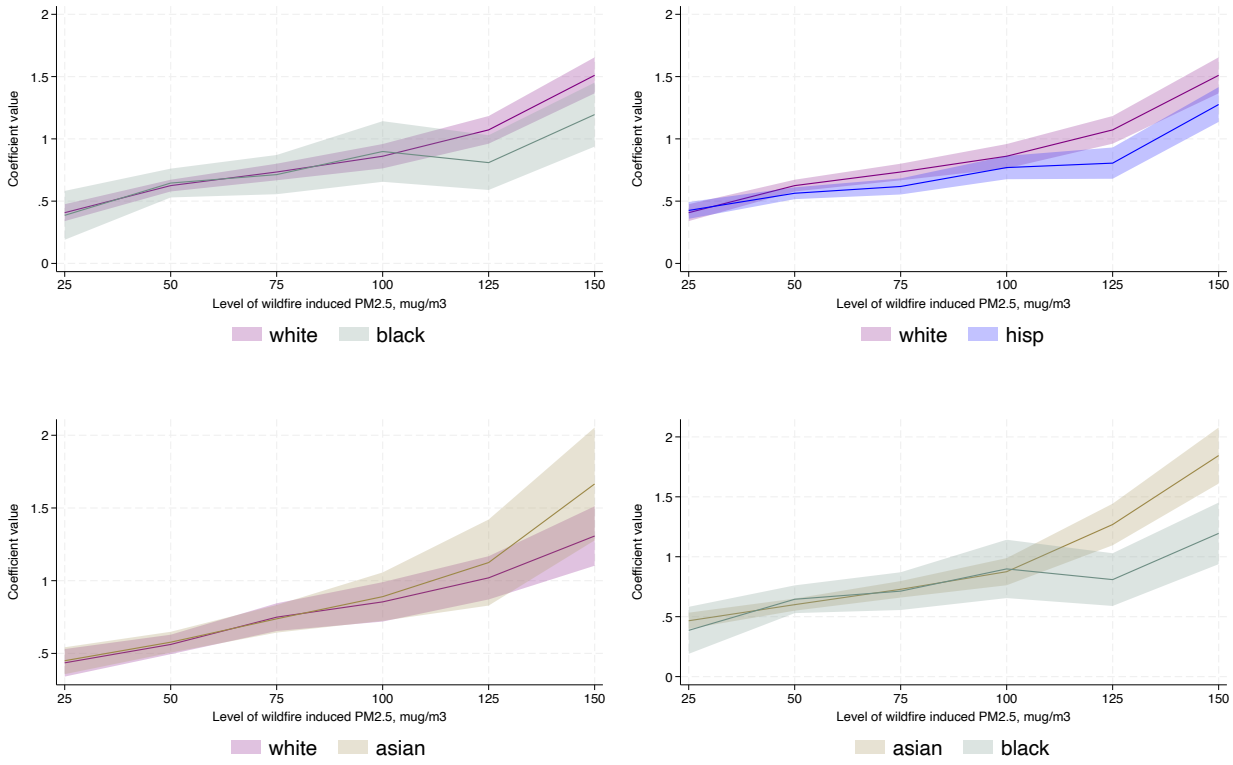


Figure 12: Distribution of Precipitation for device-Day observations

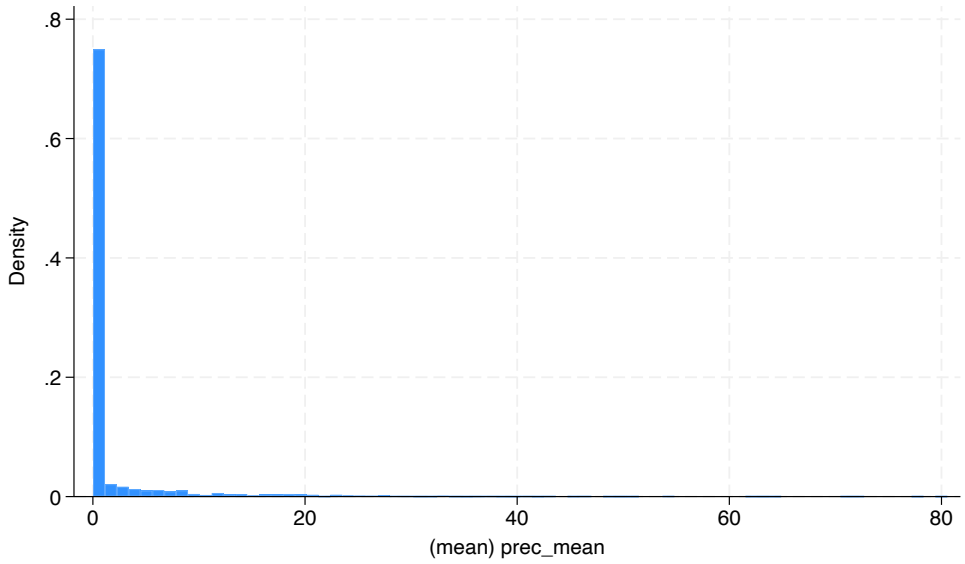


Figure 13: Event Study Outcome around on the Camp Fire in November 2018 in the Bay Area. Outcome: Hours at Home. Only if observation 10+ hours and 10+ pings in a day.

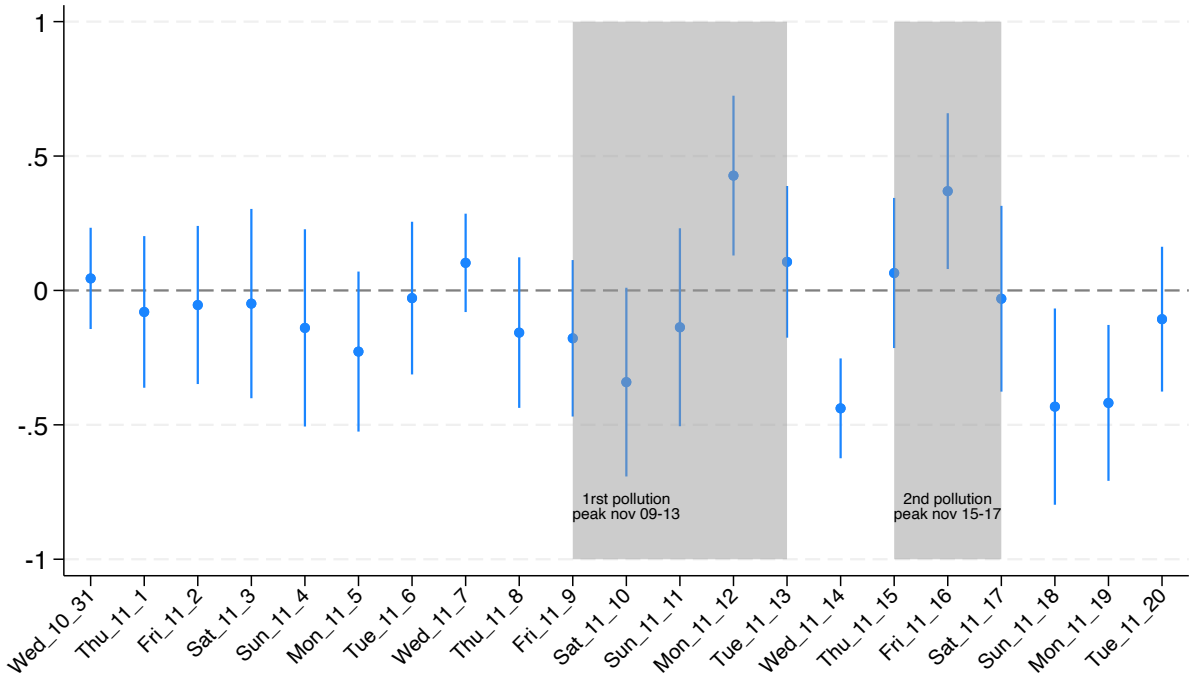
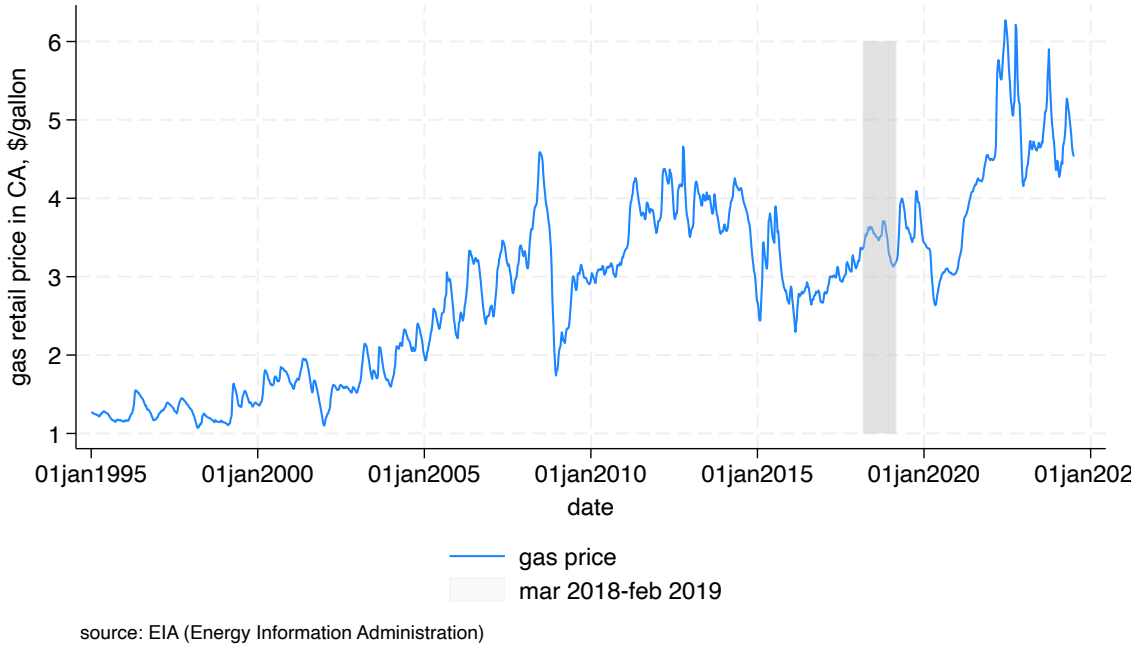
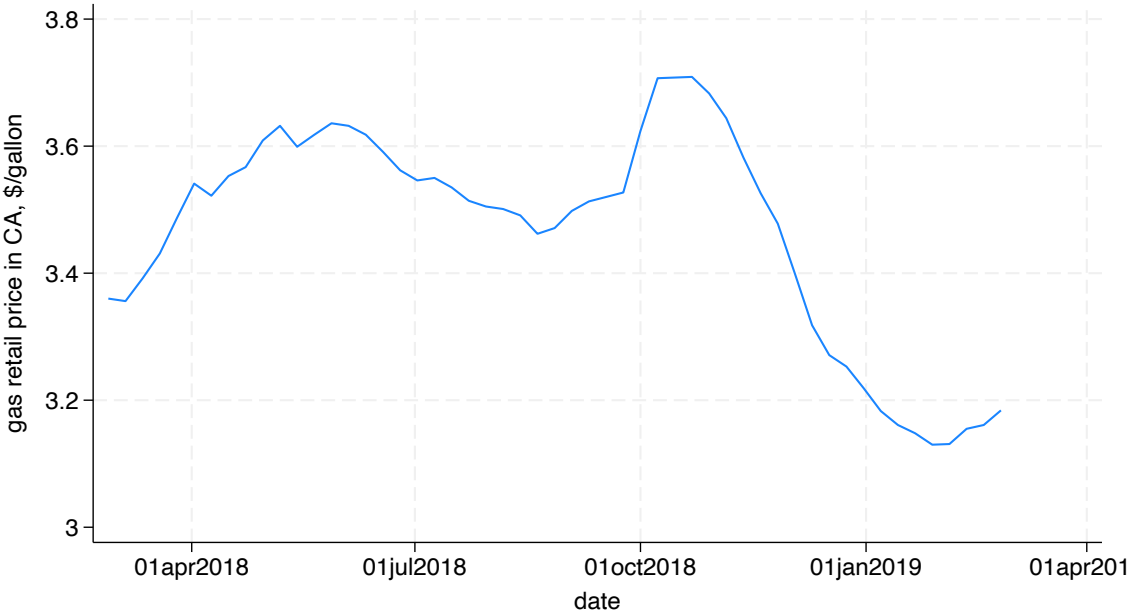


Figure 14: Evolution of California Retail Gas Prices since 1995. Mobility data sample is March 2018-February 2019.



source: EIA (Energy Information Administration)



source: EIA (Energy Information Administration)

Tables

Table 1: Distribution of device-day pollution observations

PM 2.5 bin, $\mu g/m^3$	**# device-day obs**
0-25	1.79e+07
25-50	157487
50-75	427392
75-100	166763
100-125	58817
125-150	37747
150+	23253

Table 2: Adaptation to wildfire-induced PM2.5 pollution. Baseline results.

	Hours at Home	Hours inside	Hours outside	Hours at Work	Distance travelled
	(1)	(2)	(3)	(4)	(5)
25-50 $\mu g/m^3$	-0.021	0.028	0.047***	-0.183***	0.018**
	(0.024)	(0.022)	(0.016)	(0.036)	(0.009)
50-75 $\mu g/m^3$	0.172***	0.163***	-0.103***	-0.191***	-0.057***
	(0.017)	(0.016)	(0.012)	(0.025)	(0.006)
75-100 $\mu g/m^3$	0.229***	0.219***	-0.123***	-0.095**	-0.063***
	(0.023)	(0.022)	(0.016)	(0.042)	(0.009)
100-125 $\mu g/m^3$	0.368***	0.381***	-0.157***	-0.166***	-0.034**
	(0.035)	(0.033)	(0.024)	(0.055)	(0.013)
125-150 $\mu g/m^3$	0.434***	0.360***	-0.175***	-0.206***	-0.047***
	(0.043)	(0.041)	(0.030)	(0.074)	(0.017)
150+ $\mu g/m^3$	0.893***	0.763***	-0.215***	0.027	-0.027
	(0.054)	(0.050)	(0.036)	(0.091)	(0.021)
precipitation	0.016***	0.015***	-0.013***	-0.007***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
precipitation^2	-0.000***	-0.000***	0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
temperature	-0.009*	0.038***	0.016***	0.002	0.035***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.002)
temperature^2	0.000*	-0.001***	-0.000***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Device FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Day-of-week FE	yes	yes	yes	yes	yes
cluster SE device	yes	yes	yes	yes	yes
# of devices	119170	119170	119170	26745	118333
N	8295846	8295846	8295846	1246762	8235119
R2	0.366	0.313	0.339	0.369	0.406

Notes: Only includes device-day observations for which we observe more than 10 pings throughout the day and for which we observe more than 10 hours of the day. SEs are clustered at the device level. The baseline category is days when pollution is between 0 and 25 $\mu g/m^3$.

Table 3: Varying the structure of fixed effects for baseline estimates. Outcome variable: time spent at home

	Baseline	No FEs	Device FE	Month FE	DOW FE
	(1)	(2)	(3)	(4)	(5)
25-50 $\mu g/m^3$	-0.023	0.847***	0.576***	0.237***	0.683***
	(0.024)	(0.030)	(0.024)	(0.029)	(0.030)
50-75 $\mu g/m^3$	0.170***	1.085***	0.739***	0.485***	0.923***
	(0.017)	(0.021)	(0.017)	(0.019)	(0.021)
75-100 $\mu g/m^3$	0.228***	1.169***	0.800***	0.546***	1.056***
	(0.023)	(0.028)	(0.023)	(0.027)	(0.028)
100-125 $\mu g/m^3$	0.367***	0.926***	0.650***	0.300***	1.144***
	(0.035)	(0.042)	(0.035)	(0.042)	(0.042)
125-150 $\mu g/m^3$	0.433***	1.154***	0.750***	0.503***	1.389***
	(0.043)	(0.053)	(0.044)	(0.052)	(0.053)
150+ $\mu g/m^3$	0.892***	1.508***	0.948***	0.858***	2.026***
	(0.053)	(0.065)	(0.053)	(0.064)	(0.065)
prec	0.017***	0.021***	0.008***	0.025***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prec2	-0.000***	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tAvg	-0.011**	0.001	0.121***	-0.108***	0.022**
	(0.005)	(0.009)	(0.005)	(0.010)	(0.009)
tAvg2	0.000**	0.001***	-0.002***	0.004***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Device FE	yes	no	yes	no	no
Month FE	yes	no	no	yes	no
Day-of-week FE	yes	no	no	no	yes
N	8267612	8272077	8267612	8272077	8272077

Notes: Only includes device-day observations for which we observe more than 10 pings throughout the day and for which we observe more than 10 hours of the day. SEs are clustered at the device level. The baseline category is days when pollution is between 0 and 25 $\mu g/m^3$.

Table 4: Varying clustering. Column 1: Device cluster. Column 2: datex zip cluster. Adaptation to wildfire-induced PM2.5 pollution

	hours home		hours inside		hours outside		hours at work	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
25-50 $\mu g/m^3$	-0.021	-0.021	0.028	0.028	0.047***	0.047	-0.183***	-0.183***
	(0.024)	(0.050)	(0.022)	(0.041)	(0.016)	(0.035)	(0.036)	(0.054)
50-75 $\mu g/m^3$	0.172***	0.172***	0.163***	0.163***	-0.103***	-0.103***	-0.191***	-0.191***
	(0.017)	(0.059)	(0.016)	(0.049)	(0.012)	(0.026)	(0.025)	(0.041)
75-100 $\mu g/m^3$	0.229***	0.229***	0.219***	0.219***	-0.123***	-0.123***	-0.095**	-0.095
	(0.023)	(0.074)	(0.022)	(0.073)	(0.016)	(0.028)	(0.042)	(0.068)
100-125 $\mu g/m^3$	0.368***	0.368***	0.381***	0.381***	-0.157***	-0.157***	-0.166***	-0.166***
	(0.035)	(0.077)	(0.033)	(0.075)	(0.024)	(0.046)	(0.055)	(0.054)
125-150 $\mu g/m^3$	0.434***	0.434***	0.360***	0.360***	-0.175***	-0.175***	-0.206***	-0.206**
	(0.043)	(0.131)	(0.041)	(0.126)	(0.030)	(0.065)	(0.074)	(0.082)
150+ $\mu g/m^3$	0.893***	0.893***	0.763***	0.763***	-0.215***	-0.215***	0.027	0.027
	(0.054)	(0.163)	(0.050)	(0.121)	(0.036)	(0.072)	(0.091)	(0.060)
prec	0.016***	0.016***	0.015***	0.015***	-0.013***	-0.013***	-0.007***	-0.007**
	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.003)
prec2	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000**	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tAvg	-0.009*	-0.009	0.038***	0.038***	0.016***	0.016*	0.002	0.002
	(0.005)	(0.017)	(0.005)	(0.014)	(0.004)	(0.008)	(0.007)	(0.013)
tAvg2	0.000*	0.000	-0.001***	-0.001***	-0.000***	-0.000*	-0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$_cons$	11.079***	11.079***	13.688***	13.688***	4.394***	4.394***	7.017***	7.017***
	(0.039)	(0.135)	(0.036)	(0.109)	(0.028)	(0.069)	(0.056)	(0.105)
cluster SE device	yes	no	yes	no	yes	no	yes	no
cluster SE day x zip	no	yes	no	yes	no	yes	no	yes
Device FE	yes	yes	yes	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes	yes	yes	yes
Day-of-week FE	yes	yes	yes	yes	yes	yes	yes	yes
controls (temp, prec)	yes	yes	yes	yes	yes	yes	yes	yes
# of devices	119170	119170	119170	119170	119170	119170	26745	26745
N	8295846	8295846	8295846	8295846	8295846	8295846	1246762	1246762

Notes: Only includes device-day observations for which we observe more than 10 pings throughout the day and for which we observe more than 10 hours of the day. SEs are clustered at the device level. The baseline category is days when pollution is between 0 and 25 $\mu g/m^3$.

Table 5: Time Trends versus fixed effects. Column 1: Fixed Effects. Column 2: Cubic Time Trend. Behavioral Responses to wildfire-induced PM2.5 pollution.

	hours home		hours inside		hours outside		hours at work	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
25-50 $\mu g/m^3$	-0.021	-0.068***	0.028	-0.022	0.047***	0.068***	-0.183***	-0.052
	(0.024)	(0.023)	(0.022)	(0.022)	(0.016)	(0.016)	(0.036)	(0.035)
50-75 $\mu g/m^3$	0.172***	0.125***	0.163***	0.115***	-0.103***	-0.082***	-0.191***	-0.017
	(0.017)	(0.016)	(0.016)	(0.015)	(0.012)	(0.011)	(0.025)	(0.024)
75-100 $\mu g/m^3$	0.229***	0.182***	0.219***	0.166***	-0.123***	-0.104***	-0.095**	0.030
	(0.023)	(0.023)	(0.022)	(0.021)	(0.016)	(0.016)	(0.042)	(0.039)
100-125 $\mu g/m^3$	0.368***	0.324***	0.381***	0.331***	-0.157***	-0.140***	-0.166***	-0.030
	(0.035)	(0.034)	(0.033)	(0.033)	(0.024)	(0.023)	(0.055)	(0.053)
125-150 $\mu g/m^3$	0.434***	0.389***	0.360***	0.303***	-0.175***	-0.160***	-0.206***	-0.037
	(0.043)	(0.043)	(0.041)	(0.041)	(0.030)	(0.030)	(0.074)	(0.071)
150+ $\mu g/m^3$	0.893***	0.848***	0.763***	0.705***	-0.215***	-0.198***	0.027	0.081
	(0.054)	(0.053)	(0.050)	(0.050)	(0.036)	(0.036)	(0.091)	(0.090)
prec	0.016***	0.013***	0.015***	0.013***	-0.013***	-0.009***	-0.007***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
prec2	-0.000***	-0.000***	-0.000***	-0.000***	0.000***	0.000	0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tAvg	-0.009*	-0.005	0.038***	0.013***	0.016***	0.002	0.002	-0.039***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.007)	(0.006)
tAvg2	0.000*	0.000	-0.001***	-0.001***	-0.000***	-0.000	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
cspline1		-0.144***		-0.118***		0.203***		-0.162***
		(0.011)		(0.010)		(0.007)		(0.012)
cspline2		1.038***		0.777***		-0.834***		0.165***
		(0.034)		(0.030)		(0.022)		(0.039)
cspline3		-3.741***		-2.959***		2.881***		0.104
		(0.139)		(0.123)		(0.091)		(0.166)
cspline4		2.474***		2.840***		-2.383***		-1.284***
		(0.287)		(0.259)		(0.195)		(0.361)
$_cons$	11.079***	10.566***	13.688***	13.645***	4.394***	4.368***	7.017***	7.920***
	(0.039)	(0.046)	(0.036)	(0.041)	(0.028)	(0.029)	(0.056)	(0.053)
cluster SE device	yes	yes	yes	yes	yes	yes	yes	yes
Device FE	yes	yes	yes	yes	yes	yes	yes	yes
Month FE	yes	no	yes	no	yes	no	yes	no
Day-of-week FE	yes	yes	yes	yes	yes	yes	yes	yes
# of devices	yes	yes	yes	yes	yes	yes	yes	yes
N	119170	119170	119170	119170	119170	119170	26745	27498
R2	8295846.000	8295846.000	8295846.000	8295846.000	8295846.000	8295846.000	1246762.000	1443668.000
r2	0.366	0.366	0.313	0.312	0.339	0.338	0.369	0.368

Notes: Only includes device-day observations for which we observe more than 10 pings throughout the day and for which we observe more than 10 hours of the day. SEs are clustered at the device level. The baseline category is days when pollution is between 0 and 25 $\mu g/m^3$.

Table 6: Behavioral Responses to Preciptiation. Only including device-day observations for which we observe 10 hours of data and at least 10 pings

	Hours at Home	Hours inside	Hours outside	Hours at Work	log(Distance travelled)
	(1)	(2)	(3)	(4)	(5)
2.5-5mm	0.131***	0.153***	-0.085***	-0.040**	-0.063***
	(0.011)	(0.010)	(0.008)	(0.017)	(0.004)
5-7.5mm	0.241***	0.231***	-0.115***	-0.006	-0.120***
	(0.013)	(0.012)	(0.009)	(0.024)	(0.005)
7.5-10mm	0.192***	0.178***	-0.132***	-0.039	-0.140***
	(0.015)	(0.014)	(0.010)	(0.028)	(0.006)
10-12.5mm	0.197***	0.181***	-0.103***	0.004	-0.131***
	(0.018)	(0.017)	(0.013)	(0.032)	(0.007)
12.5+mm	0.184***	0.116***	-0.181***	-0.090***	-0.193***
	(0.011)	(0.010)	(0.008)	(0.018)	(0.004)
smokePM_pred	0.003***	0.003***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
tAvg	-0.003	0.044***	0.012***	0.001	0.033***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.002)
tAvg2	0.000	-0.001***	-0.000***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
cons	11.014***	13.623***	4.429***	7.012***	1.223***
	(0.039)	(0.036)	(0.028)	(0.057)	(0.013)
cluster SE device	yes	yes	yes	yes	yes
Device FE	yes	yes	yes	yes	yes
Month FE	yes	yes	yes	yes	yes
Day-of-week FE	yes	yes	yes	yes	yes
# of devices	119170	119170	119170	26741	118333
N	8295846	8295846	8295846	1246762	8235119
R2	0.366	0.313	0.339	0.369	0.406

Notes: Only includes device-day observations for which we observe more than 10 pings throughout the day and for which we observe more than 10 hours of the day. SEs are clustered at the device level. The baseline category is days when rainfall is between 0 and 2.5mm.

Table 7: Elasticity of time-use to changes in gas prices. Weekly retail gas prices in $ per gallon.

	Hours at Home	Hours inside	Hours outside	Distance travelled
	(1)	(2)	(3)	(4)
weekly gas price	1.298***	0.911***	-0.648***	-0.239***
	(0.072)	(0.069)	(0.048)	(0.032)
avg. temp	0.002	0.003*	0.004***	0.005***
	(0.002)	(0.002)	(0.001)	(0.001)
Device FE	yes	yes	yes	yes
Month x tract FE	yes	yes	yes	yes
# of devices	118116	118116	118116	117290
N	2273702	2273702	2273702	2258101

Table 8: Quantification of the Behavioral Change Induced by PM2.5 from Wildfires in terms of $ per gallon price of retail gasoline

	Coef on gas price	Coef on a day at 150+ $\mu g/m^3$	An additional day at 150+ $\mu g/m^3$ is equivalent to a ... increase in $ per gallon of retail gasoline
Hours inside	0.911	0.763	0.83
Hours home	1.3	0.893	0.69
Hours outside	-0.648	-0.215	0.34
Log (distance travelled)	-0.239	-0.027	0.19

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