Impacts of wildfire-season air quality on park and playground visitation in the Northwest United States

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Abstract

A significant cost of wildfires is the exposure of local and regional populations to air pollution from smoke, which can travel hundreds of miles from the source fire and is associated with significant negative health consequences. Wildfires are increasing in frequency and intensity in the United States, driven by historic fire management approaches and global climate change. These influences will take many decades or longer to reverse, so the main opportunities for mitigating health effects involve minimizing human exposure through changes in behavior or infrastructure. One key recommendation for reducing pollution exposures during wildfire smoke events is to limit time and physical activity outdoors, but there is limited evidence on the extent to which people make this change. We estimate how use of parks and playgrounds changes with air quality during wildfire season in the northwest United States. We find small reductions in park and playground visits on moderately polluted days, and large reductions, to 50-60% of baseline visits, when pollution levels are high. Disaggregating results by neighborhood characteristics, we find a significantly greater behavioral response to moderate levels of air pollution in neighborhoods with higher socio-economic status, although responses to high levels of pollution are similar across neighborhood types.

1. Introduction

Wildfire seasons are growing more intense and longer in duration due to climate change and land management practices (Abatzoglou and Williams 2016; Brotons et al. 2013; Steel, Safford, and Viers 2015). While this is a global phenomenon, communities in the western United States are among those experiencing impacts ranging from episodic smoke exposure to catastrophic wildfire events. A significant cost of wildfires is the exposure of the local and regional population to air pollution from smoke, which can travel hundreds of miles from the source fire (Burke et al. 2021). Exposure to wildfire smoke is associated with acute respiratory symptoms and increased rates of hospitalizations (Liu et al. 2017; Moeltner et al. 2013); and evidence is growing that it also affects long-term cardiovascular and respiratory health as well as birth outcomes (Abdo et al. 2019; Holstius et al. 2012; Rosales-Rueda and Triyana 2019) and mental health (To, Eboreime, and Agyapong 2021). Fine particulate matter (particulate matter less than 2.5 microns in diameter, $PM_{2.5}$) is a key component of wildfire smoke implicated in these effects; when inhaled, $PM_{2.5}$ can travel deep into the lungs, causing inflammation and a wide range of health impacts across the life course. There is also evidence that the composition of wildfire smoke is more damaging to health than pollution from other sources with equivalent concentrations of $PM_{2.5}$, particularly when structures are burned (Aguilera et al. 2021; Balmes 2018; Xu et al. 2020).

Health impacts of wildfire smoke vary by demographic and socioeconomic characteristics, and by prior smoke events (Kondo et al. 2019; Heft-Neal et al. 2022). Unlike the urban air pollution context, in which differences in impacts may be explained by socioeconomic disparities in exposure (Gray, Edwards, and Miranda 2013; Goodman et al. 2011; Currie, Voorheis, and Walker 2020), evidence suggests that exposure to wildfire smoke is similar across socio-economic groups (Burke et al. 2021), implying that heterogeneity in outcomes occurs for other reasons (Davies et al. 2018). One potential determinant of differences in health outcomes is the degree to which people take action to reduce air pollutant exposures during wildfire events. Recommended protective actions include staying indoors with windows and doors closed and reducing activities that generate indoor air pollutants (e.g., vacuuming or use of certain cooking methods); using portable air cleaners; limiting strenuous activity; and wearing N95 respirators (US Environmental Protection Agency 2019; 2020). Guidelines emphasize the importance of preventive actions for vulnerable populations, such as older adults, pregnant people, and young children (US Environmental Protection Agency 2020). Surveys suggest that many people are aware of these recommendations, and that that a majority report taking some exposure reduction action (Richardson, Champ, and Loomis 2012; Rappold et al. 2019). Data from social media posts and internet searches also indicate that people are less happy during wildfire smoke events, and that they seek information on air quality and potential protective technologies such as air purifiers and face masks when such events occur (Burke et al. 2022). However, there remains limited observational evidence on the extent to which people take particular actions, and the contexts in which they do so.

We know that people take averting action when exposed or alerted to urban air pollution. Numbers of pedestrians and cyclists decrease when pollution levels are high, particularly for trips that are likely to be related to leisure rather than work (Choi, Yoon, and Kim 2019; Saberian, Heyes, and Rivers 2017). People are observed to respond to air pollution information with lower visitation to leisure-related locations such as zoos and sports events (Graff Zivin and Neidell 2009; Janke 2014; Yoo 2021), and reductions in overall strenuous outdoor activity (Ward and Beatty 2016). Consumer data from Chinese cities show increases in purchases of face masks and portable air cleaners when pollution is high, with stronger effects in higher-income locations (Sun, Kahn, and Zheng 2017; Junjie Zhang and Mu 2018; Ito and Zhang 2020). Averting responses to wildfire smoke are likely to differ from responses to pollution from sources such as industrial activity and transportation. The latter are primarily of concern in large urban areas, whereas wildfire smoke can affect people at all points on the urban-rural continuum and will often be most severe in less populated regions with high forest density (Davies et al. 2018). There is evidence that preventative health behaviors differ in rural compared with urban areas (Matthews et al. 2017). In addition, the density of air quality monitors is typically lower outside of large cities (Watson et al. 1997), so people exposed to wildfire smoke may have access to less, or lower quality, information on the level of pollution at their specific location. The temporal patterns of wildfire smoke and industrial and transport-related pollution also differ. Wildfire season in temperate regions such as North America and Europe typically coincides with summer, a time when people are more likely to spend time outdoors. Urban sources tend to generate consistent air pollution with relatively limited fluctuation, whereas pollution from wildfire smoke may be low for much of the fire season, with episodic spikes that can be very high (Childs et al. 2022).

While we would expect responses to pollution from smoke to be different from responses to pollution from industrial or other sources, less is known about averting behavior in the context of wildfire smoke. An evidence base is emerging; for example, Burke et al (2022) use cellphone mobility data to determine that US residents are less likely to leave their home on smoke-affected days, with strong responses at relatively low levels of $PM_{2.5}$ exposure. They also find some evidence that people leave their residence altogether when smoke levels are particularly high. Gellman et al. (2022) use data on reservations at US public campgrounds, and find only a small reduction in campground use with proximity to, or smoke from, wildfires. Rosenthal et al. (2020) observe significant reductions in step counts on days with high air pollution during the 2017 and 2018 California wildfire seasons. The conflicting findings so far about the magnitude of responses to smoke suggest differences in willingness or ability to take averting actions across different types of behaviors, and perhaps across individuals. Our first contribution to this literature is to use a novel dependent variable, visitation at public parks, to estimate the degree to which people reduce a common type of outdoor activity on days with poor air quality during wildfire season. Reducing time and activity outdoors is a key element of the public health guidance for wildfire smoke events, particularly for children and adolescents (US Environmental Protection Agency 2015). As with campground use, variation in park use is likely to largely capture discretionary recreational activity as opposed to required work activity outdoors, although it is less likely to be planned in advance. In addition, we contribute to the literature on how people respond to pollution from wildfires by separately estimating effects for the playground areas within our sample parks, which we expect to primarily reflect actions taken by carers of young children; and by examining heterogeneity in the behavioral response by income and education level, city size, and air quality in the prior week.

We estimate an averting response to air pollution during wildfire season in the northwest United States. In this region alone, 5,800 fires totaling 2.7 million acres burned in 2021, which represents 38% of burned area in the United States and is more than double the area burned in the region in 2011 (Insurance Information Institute 2021). In the United States as a whole, wildfires are an important source of air pollution, and becoming the primary source, as urban air quality improves and wildfire frequency and intensity increase with high fuel loads and climate change (Burke et al. 2021; Clay, Muller, and Wang 2021). We estimate the effect of air quality on park and playground visitation during the main wildfire season in cities of different sizes in the states of Washington, Oregon, Idaho and Montana. Although we include total air pollution from all sources rather than from wildfires alone, seasonal comparisons show that air quality is almost always Good outside of wildfire season at these study sites, indicating that the pollution we observe is largely attributable to fires. Visitation is measured using the number of mobile devices recorded within park boundaries by the Near Vista platform. We use a Poisson model with spatial and temporal fixed effects to examine how park use changes on days with moderate or high levels of $PM_{2.5}$ relative to days with low levels. Overall, we see reductions in park visits as air quality deteriorates. On days with $PM_{2.5}$ categorized as Moderate or Unhealthy for Sensitive Groups, observed devices within park boundaries average around 90% of the number on Good days. Visits fall to 80% of the baseline rates on days categorized as Unhealthy, and 60% of baseline on days classed as Very Unhealthy or Hazardous. Disaggregating results by neighborhood characteristics, we find that individuals in all neighborhoods reduce park use by similar amounts when air quality is Very Unhealthy or Hazardous, but only the parks used by communities with high levels of income and education see substantial reductions in use when air quality is Moderate or Unhealthy for Sensitive Groups.

Understanding averting responses to wildfire smoke is particularly important because the trends in wildfire frequency and intensity will take many years to respond to policy intervention. One major driver is climate change, which requires global policy action to slow or reverse. The other is the history of fire suppression which can be addressed through prescribed burning, but only over a timescale of decades or longer (Finney et al. 2007). As a result, the policy levers available to reduce the negative health effects of wildfire smoke are primarily those that reduce exposure through changes in behavior or infrastructure. Understanding the actions that people take to limit their own exposure, and the circumstances in which people do not take recommended actions, is a prerequisite for design of interventions to limit the negative consequences of air pollution from wildfires. In addition, as with other environmental exposures, the total costs of wildfire smoke consist of the health costs plus any costs associated with averting behavior (Graff Zivin and Neidell 2013). Knowledge of the type and amount of averting behavior that people engage in to reduce health impacts of wildfire smoke is therefore needed when estimating the economic costs of wildfires to inform fire management decisions (Kochi et al. 2010; Bayham et al. 2022).

2. Data

Our dependent variable is the number of visits to individual parks and playgrounds in the northwest United States, estimated using the locations of mobile devices (such as cellphones) relative to park or playground boundaries. We use daily counts of mobile device 'visits' to each sample location during the months of June, July, August and September of 2020 and 2021. We merge daily particulate matter ($PM_{2.5}$) estimates at a 1-km resolution with our parks and playgrounds by polygon. We also merge additional information on daily weather conditions and state-level stay-at-home orders related to the COVID-19 pandemic by date and polygon.

2.1 Study area

Our study area includes the states of Idaho, Montana, Oregon and Washington. Each of these states ranked in the top six within the United States for acres burned by wildfires in 2021 (Insurance Information Institute 2021). The typical timing, duration and characteristics of wildfire season are similar across these states. However, there is considerable spatial and temporal variation in occurrence and intensity of fires and smoke within each season in the region. There is also variation in population density and socio-economic and demographic characteristics. The 13 cities included in the analysis are displayed in Figure 1. These cities were selected to capture variation in biophysical zone, defined using two-digit hydrologic units in the northwestern portion of the United States: 1) Missouri and 2) Pacific Northwest. To ensure a range of city sizes, we also stratified by small (less than 100,000), midsize (less than 250,000 and greater than or equal to 100,000), and large (250,000 or more) populations–as determined by the U.S. Department of Education (National Center for Eduation Statistics 2006).

Spatial extents of parks and playgrounds within the sample cities were acquired from the U.S. ParkServe® Dataset (Trust for Public Lands 2022). This dataset contains separate shapefiles for parks and the playgrounds falling within park boundaries. We included all parks that also contain playgrounds in each of the sample cities in the study. Park characteristics vary widely from city plazas to wildlands, and the frequency of different park types is likely to differ across states and between city types, which could introduce bias to our estimated effects if users of different spaces respond to air pollution in different ways. We therefore limit the sample of parks to those that (i) contain playgrounds (and therefore exclude very small greenspaces, linear greenways and large wildland areas) and (ii) fall within city boundaries. This creates a broadly comparable set of parks for which we can interpret our findings. Averting responses are likely to be different for different types of users e.g. commuters using greenways; sports teams using athletic facilities; or people on multi-day trips in wildland areas. Rather than combining all of these, our analysis allows us to better understand changes in recreational activities that occur in the types of urban parks that exist across all the cities in our sample. For the purposes of our analysis, we remove the playground extents from their respective, encompassing park extents using the Erase tool in ArcGIS Pro. Therefore, visitation within the playgrounds is assessed separately from visitation within the surrounding park, as one aim is to evaluate responses to wildfires by carers of young children relative to the wider population.

2.2 Park and playground visits

We use the number of unique mobile devices observed within a park or playground boundary on a given day to measure park and playground visitation. Rather than interpreting this as the number of people visiting the location, we use these data to capture *variation* in daily visitation. Mobile device location data is increasingly used in such a manner in park and outdoor recreation research (see review by Whitney et al. 2022), as well as in other contexts such as responses to Covid-19 (Couture et al. 2022; Xiong et al. 2020) and movements of refugees (Beine et al. 2021). Such data can be obtained from a number of vendors that both aggregate and anonymize location data. Data for this study come from the Near Vista platform, which captures information from a sample of about 30% of United States cellphone users (Lawson 2021), and has been previously used in a similar parks context (Rice et al. 2022). These data are gathered using Software Development Kits which are embedded into device web browsers and other applications (e.g., weather apps, way-finding apps, etc.) with whom device users elect to share their location (Near 2021). As of 2021, Near reported over 100,000 applications from which its panel of location data was drawn (Near 2021).

The historic location of devices within Near's panel can be aggregated within a defined spatial extent (e.g., a park or playground) for a given window of time (in our case, one day). Additionally, the common evening location of a device (i.e., where a device spends the majority of its nights throughout the year) is recorded for all devices observed within this defined spatial extent, and the demographics of that common evening location (measured at the US Census block group-level) can be used as a proxy for estimating users' socio-economic and demographic characteristics. We extract mobile device location data for all parks containing playgrounds and their respective playgrounds within each of the 13 cities included in the study. Extracted data include the number of unique devices visiting each park and playground for every day of the 2020 and 2021 wildfire seasons (June 1st through September 30th). Additionally, the common evening locations for each day's visitors are recorded and tabulated separately for each park and playground. The common evening locations are reported as the annual proportions of visitors to each park and playground from each census block group (Near 2021; Rice et al. 2022). Demographic data from the 2016-2020 American Community Survey are linked with each park or playground based on the census block groups from which visitors come, to understand the population served by each park and classify parks based on the average income and education levels of their visitors' neighborhoods.

The average count of unique mobile devices observed per day within the parks in our sample is 28 and the average count within playgrounds is 7.6 (Table 1). However, the absolute values are not very meaningful as our data only include a proportion of the total number of devices, and the number of devices only represents a proportion of the total number of people as some visitors may not have mobile devices with them, particularly if they are young children. We therefore focus on how the relative number of devices varies with daily air quality and other factors. Rice et al. (2022) ground-truth the representativeness of campsite visitors' common evening locations (as acquired from Near) with population-level home locales (zip codes) of campsite visitors (obtained through reservation records), and find high levels of spatial correlation (ranging from .860 to .995) across all five campgrounds in their study. Near (2022) show that, while overall correlation between recorded common evening locations is high (Pearson correlation coefficient of 0.97), their sample slightly overrepresents those with incomes of \$25,000-\$50,000 and slightly underrepresents those with low (< \$10,000) or high (> \$75,000) incomes. In addition, people over 60 years of age and those who did not finish high school are slightly underrepresented.

Figure 2 shows the weekly median and upper- and lower-quartile counts of observed devices in parks during the period June-September in 2020 and 2021 for each state in our study area. The median device counts are similar for each state, but the upper-quartile counts are typically higher in Oregon and Washington because these states have large cities, with a small number of heavily visited parks, which Idaho and Montana do not. The data for 2020 in all four states show increases in park visits in early June, followed by fairly consistent counts until decreases are observed in September. In 2021, we see increases in park visits in early-July; a drop in visits in August; and some resurgence in September to differing degrees in all four states. Within these weekly patterns, there is considerable daily variation in park visitation.

2.3 Air quality

We use daily 1-km resolution maps of surface $PM_{2.5}$ for the western United States from 2003 - 2021 (Swanson et al. 2022). These $PM_{2.5}$ layers were created using average daily US Environmental Protection Agency (EPA) Air Quality Station monitoring observations (US Environmental Protection Agency 2012) fit through a geographically weighted regression model. Variables in the regression model included daily Moderate Resolution Imaging Spectroradiometer (MODIS) aerosol optical depth (AOD) satellite data (Lyapustin et al. 2018), and meteorological conditions, human activities and local topography combining to account for the impacts of stagnant air and inversions. Use of these modeled $PM_{2.5}$ estimates enables us to account for the fine-scale variation in air quality between parks located in the same city, which would not be captured with data obtained directly from the sparsely distributed EPA monitors themselves (Filonchyk, Peterson, and Sun 2022).

The daily 1-km^2 $PM_{2.5}$ data are averaged across the boundaries of the census block group in which the park or playground is located, as provided by the US Census Bureau. We use the 'extract' function from the *exactextractr* package (Baston, ISciences, and Baston 2022) in R (R. Core Team 2016) to calculate the daily census block group $PM_{2.5}$ averages, weighted by the percent of each 1-km pixel contained within respective boundaries. These $PM_{2.5}$ daily averages are linked with the park and playground visitation observations based on the census block group of the park. Figure 2 shows the mean $PM_{2.5}$ concentrations in μg/m^3 and median number of mobile devices observed in sample parks during the period June-September in 2020 and 2021 for each state in our study area. Air quality was relatively good in June and July of 2020 in all four states, with deterioration in mid-August in Idaho and Montana and in September in Oregon and Washington. Poor air quality was observed for much of the fire season in 2021: from early-July in Idaho and Montana and from early-August in Oregon and Washington. The park visit data shows fluctuation over the weeks and months of the fire seasons in each state and year. Decreases in park visits are observed to fall during particularly strong peaks in $PM_{2.5}$, especially in Oregon and Washington. However, it is evident that there are other influences on visit frequency over time and space which are necessary to control for in our analysis.

For our main analyses, we transform the continuous estimate of $PM_{2.5}$ concentrations in the census block group surrounding each sample park into an ordinal variable corresponding to the levels of the US Air Quality Index (AQI) for $PM_{2.5}$ developed by the US EPA (US Environmental Protection Agency 2018). This transformation allows us to interpret our results in the context of the information available to the public about air quality and its health effects. The levels of our ordinal variable are: Good ($PM_{2.5}$ concentrations of 0-12μg/m^3), Moderate ($PM_{2.5}$ concentrations of 12.1-35.4μg/m^3), Unhealthy for Sensitive Groups ($PM_{2.5}$ concentrations of 35.5-55.4μg/m^3), Unhealthy ($PM_{2.5}$ concentrations of 55.5-150.4μg/m^3), Very Unhealthy or Hazardous ($PM_{2.5}$ concentrations greater than 150.4 μg/m^3). We combine the Very Unhealthy and Hazardous categories because of the small number of observations with daily $PM_{2.5}$ concentrations at either level. We can see from Figure 3 that the majority of park-days in all states and months in our sample have Good air quality, and all days observed in June are recorded as Good. Moderate air quality is observed frequently in Idaho and Montana in July, August and September and less frequently in Oregon and Washington. A small number of days are observed as Unhealthy for Sensitive Groups or Unhealthy in each state, with most occurrences in August and September. Days with a 24hr mean of Very Unhealthy or Hazardous air quality are primarily observed in Oregon and Washington in September (specifically September 2020), and infrequently in Idaho and Montana.

We use estimates of total $PM_{2.5}$ rather than estimates for wildfire-specific $PM_{2.5}$ (e.g. Childs et al. 2022, Zhang et al. 2023) because the Swanson et al (2022) data are calibrated for the topography, climate and sparse monitoring network of our study region. Specifically, the model was developed to capture the spatial variation in air quality resulting from inversion and drainage flow features common in the Intermountain West, particularly during wildfire season (Swanson et al. 2022). In addition, the total $PM_{2.5}$ data are available at a finer spatial resolution than current publicly available wildfire-specific $PM_{2.5}$ datasets, which allows us to capture variation between parks. Figures 2 and 3 support our underlying assumption that the variation in $PM_{2.5}$ during the summer months in our study cities is primarily attributable to wildfire smoke rather than to industrial and transportation-related sources. As noted above, in all states, $PM_{2.5}$ falls in the Good category for all weeks in June. The Northwest Annual Fire Reports for 2020 and 2021 describe minimal fire activity in June in Washington, Oregon and Idaho, with substantial increases from July through September (Northwest Interagency Coordination Center 2020; 2021). In principle, we would expect behavioral responses to total $PM_{2.5}$ rather than solely the proportion derived from wildfire smoke. However, as the focus of the study is on responses to wildfire-specific $PM_{2.5}$, we test the robustness of our assumption that wildfires are the primary source of $PM_{2.5}$ in the season and locations we examine by limiting analysis to the Small and Midsize cities, where other sources of pollution are more rare.

In principle, travel to parks (or lack of travel to parks) could influence air quality. However, it is unlikely to have a large enough effect to move $PM_{2.5}$ from one AQI category to another. As noted in the previous paragraph, during the month of June when wildfires were not active, we observe zero days with AQI values that are categorized as worse than “Good”. This indicates that total vehicle use occurring in our sample cities does not generate enough air pollution to reach the “Moderate” category. According to the National Household Travel Survey, only 2.6% of all U.S. vehicle miles traveled are for any form of recreation (Federal Highway Administration 2022), of which a subset represents travel to urban parks and playgrounds, many of which are within walking distance of individuals’ homes. Therefore, we do not view the effect of travel to parks on air quality as a sufficiently large source of endogeneity to influence our results.

2.4 Other independent variables

Daily weather station data for each of the study sites were obtained from the Global Historical Climatology Network (GHCN)-Daily (National Centers for Environmental Education 2022). Based on the geocoded location of each weather station and park centroid coordinates, we assigned each park and playground a daily minimum temperature, maximum temperature, and precipitation amount. These observations were taken from the closest weather station in euclidean distance, although the exact weather station used was allowed to change daily given that weather variables could have missing values from certain weather stations. We also compare specifications using daily estimates for each park centroid of maximum temperature, precipitation, and vapor pressure deficit from Parameter-elevation Regressions on Independent Slopes Model (PRISM). Vapor pressure deficit is one approach for quantifying humidity. The PRISM Climate Group at Oregon State University publishes daily and monthly gridded climate datasets at the 4km resolution for the conterminous US using weather station data combined with elevation, coastal effects, temperature inversions, and terrain barriers (PRISM Climate Group 2024).

Stay-at-home orders related to the SARS-CoV-2 outbreak were in effect in some areas during the first portion of 2020. Using data collected by the COVID-19 US State Policy (CUSP) database (Raifman et al. 2020), we include a binary variable indicating whether a state-wide stay-at-home/shelter-in-place order was in effect on the given date. Oregon's order remained in effect the longest, ending on June 19, 2020. Washington's order ended on Jun 1, 2020, and orders for Montana and Idaho ended April 26 and May 1, respectively, both of which are before our data begin.

For analysis of heterogeneity in the impact of air quality on park use, we categorize parks based on the income and education levels of the neighborhoods their visitors come from. Each mobile device is associated with a common evening location, which is typically the user's home address (Rice et al. 2022; UberMedia 2021). This is used to estimate the proportion of visitors to a given park or playground who live in each of the census block groups from which visitors to that site are drawn during the year. We use these proportions, in combination with 2016-2020 American Community Survey data on the shares of the block group populations with income of > $75,000/year and the shares with at least some college education, to create weighted averages of income and education levels in the home neighborhoods of visitors to each park in our sample. This does not tell us the characteristics of individual park visitors, but allows us to compare parks that largely serve residents of higher income or higher education neighborhoods with those that serve residents of lower income or lower education neighborhoods. To estimate the regression models, we assign parks to terciles of 'high', 'medium' and 'low' neighborhood income and education, using the 2020 and 2021 weighted averages of visitor common evening locations described above.

We also define parks as located in Small, Midsize or Large cities for the heterogeneity analysis. Small cities have a population of less than 100,000, Midsize cities have a population of between 100,000 and 250,000, and Large cities have a population greater than 250,000.

3. Empirical Strategy

We estimate the effect of air quality on park visitation, measured using the number of mobile devices recorded by the Near Vista platform. As our dependent variable is nonnegative and highly dispersed, we use a Poisson specification, with the following conditional mean:

$$E[Visits_{it}|AQ_{it}, \boldsymbol{X}_{it}, \alpha_i, \delta_t] = \alpha_i \exp\left(\beta AQ_{it} + \boldsymbol{X_{it}}\gamma + \boldsymbol{\delta_t} + \varepsilon_{it}\right) \qquad \text{(Equation 1)}$$

The count of park visits, $Visits_{it}$, is a function of the air quality, AQ_{it}, in a given park on a particular day, conditional on park (α_i) a vector of time ($\boldsymbol{\delta_t}$) fixed effects and a vector of time varying controls such as weather and restrictions implemented to reduce the spread of Covid-19 ($\boldsymbol{X}_{it}$). The number of recorded mobile devices is not a count of the number of people in the park, as not everyone carries a mobile device and not all devices share data with Near. The use of the fixed-effects pseudo-Poisson maximumum likelihood model allows us to focus on the *change* in devices on days with poor air quality relative to days with good air quality, which we use to approximate the change in visits.

The fixed-effects pseudo-Poisson maximum likelihood model has the advantage of being consistent under general distributional assumptions, provided that the conditional mean is correctly specified (Wooldridge 1999). In our case, the distribution of the dependent variable approximates an exponential function, with around 6% of observations taking a value of zero, many low values, and few large values. Given this distribution, the Poisson specification is suitable as long as robust standard errors are specified to account for overdispersion (Wooldridge 2010). We estimate all models with cluster robust standard errors at the park or playground level. We use the package PPMLHDFE in Stata 17 to estimate Pseudo-Poisson Maximum Likelihood with High Dimensional Fixed Effects for all models, enabling the inclusion of unit and time fixed effects and their interactions (Correia, Guimarães, and Zylkin 2020).

We include spatial fixed effects to control for potential spatial correlation between average air quality through the fire season and rates of park visitation across different parks. Our preferred specification uses park or playground fixed effects, and alternative specifications use county or state fixed effects. We also use year, month and day-of-week fixed effects to control for temporal correlation between the periods within the fire season when fire activity is typically high and times when people are more likely to be outdoors, for example because of school schedules or vacation travel. Our preferred specification includes state-specific time fixed effects and day-of-week fixed effects that vary by month.

Air quality is a categorical measure reflecting the guidance issued by the EPA and other organizations about the appropriate actions to take in different air quality conditions. This allows us to estimate nonlinear responses depending on the severity of the air pollution. We control for weather related effects using the daily high temperature (in degrees fahrenheit) and total precipitation (in inches). These are included in quadratic form to account for nonlinear effects. For example, people may initially spend more time outside as temperatures increase, but return to indoor locations on very hot days. Our data spans the early months of the Covid-19 pandemic in 2020 when some states had stay-at-home orders from their governors' offices, reducing what may have otherwise been higher visitation days. We include state-level Covid-19 restrictions as time varying covariates to control for any biases resulting from this variation.

Difference between states in prevalence of, and cultural attitudes to, Covid-19 persisted after formal regulations were lifted, which may also have influenced the patterns of park use. Our preferred specification therefore includes month-by-state and year-by-state fixed effects to control for these potential spatial patterns in the influence of Covid-19. These also control for other sources of spatial and temporal variation in park use such as differences in seasonal patterns of tourism across states that may be correlated with spatial and temporal variation in seasonal patterns of fire and smoke activity. The month fixed effects also control for effects such as public holidays and school vacations that are similar across the whole study region, while the year fixed effects capture any general trends in park use. The other main temporal influence on park visitation is the day of the week, particularly as weekdays may differ from weekends. In our preferred specification, we include 'day-of-week'-by-month to allow for different weekly patterns of use during school vacations and peak tourist seasons relative to months when most people are at school or work.

We use city and neighborhood characteristics to assess heterogeneity in the behavioral responses to air quality. We do not have information on the individual characteristics of park visitors. However, we do have annual frequencies for common evening locations of observed devices for each park. We use weighted averages of the demographic characteristics of these common evening locations to approximate the average income and education levels of the neighborhoods from which the visitors to a particular park typically come. We interact these neighborhood characteristics with the categorical measure of air quality to explore whether behavioral responses to air pollution differ between parks that serve high vs. low-income neighborhoods or neighborhoods with high vs. low average levels of education. We also interact air quality with city-size to explore whether responses are different in small, midsize and large cities, as the characteristics of parks and the ways in which they are used are likely to vary. Our measures of income and education vary by park, but only minimally within parks (i.e. one observation per year), and city size varies by city, but not by park within a city. We therefore use county fixed effects instead of park fixed effects to estimate these interactions. We confirm using the main specifications that the results do not vary substantially with the level of the spatial fixed effects.

4. Results

We estimate the effect of air quality on park visits (Table 2a and Figure 4a) and playground visits (Table 2b and Figure 4b). We also estimate heterogeneous effects by city and neighborhood characteristics (Figure 5) and test for robustness of our findings to key modeling choices (Table 3). These results are described below.

Results are presented as incidence rate ratios (IRR) of observed devices on days when air quality is not categorized as Good relative to days when air quality is categorized as Good, under alternative specifications as described above. The IRR is obtained by exponentiating the coefficients of the Poisson models and can be interpreted as the rate of visitation (number of observed devices per day) at each AQI category relative to the baseline rate of visitation on Good days. All specifications include quadratics for temperature and precipitation and an indicator variable for whether a Covid-19 stay-at-home order was in place in the observed county on the day of the observation. Models are estimated using standard errors clustered at the park level.

4.1 Park visitation

Across all specifications, observed devices are significantly lower on days that do not have Good air quality. All except for model (1), with state fixed effects, show consecutively increasing reductions in park visitation as the severity of air pollution increases through each of the categories from Good to Very Unhealthy/Hazardous. The magnitude of the effects is very similar at each level of air quality for models (2)-(4), with county or park fixed effects. As noted, they differ in the model with state fixed effects (1), which is likely to be result of spatial patterns of population density, which influences park visitation rates, and frequency of smoke events. Our preferred specification is model (4), with park, state-by-month, state-by-year, and month-by-day of week fixed effects. On days with Moderate air quality, the number of devices observed on average in a sample park is 0.94 times the base rate, i.e. the number of devices observed in the same park on days with Good air quality. It is slightly lower, at 0.9 times the base visitation rate, on days that are categorized as Unhealthy for Sensitive Groups. On Unhealthy and Very Unhealthy/Hazardous days, visits fall on average to 0.78 and 0.62 times the base rate respectively. Based on the mean number of observed mobile devices (28.4), this translates to approximately 1.7 fewer devices on "Moderate" days; 2.8 fewer on Unhealthy for Sensitive Groups days; 6.2 fewer on Unhealthy days; and 10.8 fewer on Very Unhealthy/Hazardous days in the mean park, although these numbers would be lower for less-visited parks and substantially higher for the most-visited parks. These numbers of observed devices cannot be directly translated to numbers of visitors because we do not have data on the exact number of visitors that the mobile devices represent, although it is estimated to be approximately 30% of United States cellphone users (Lawson 2021).

Figure 4a, which plots these effects, highlights the nonlinear relationship between the levels of AQI and park visitation. The difference between the number of observed devices on days with air quality that is Moderate vs. Unhealthy for Sensitive Groups is not statistically significant at the 5% level (although both are significantly lower than Good days). We do see a statistically significant drop in observed devices as air quality worsens from Unhealthy for Sensitive Groups to Unhealthy, and a larger and more significant decrease between the Unhealthy and Very Unhealthy/Hazardous categories.

4.2 Playground visitation

We estimate equivalent specifications to estimate observed devices within the boundaries of playgrounds as a function of $PM_{2.5}$ AQI category. This is intended to primarily reflect visits by caregivers of the young children as a point of comparison with the broader population of park users. Young children are more sensitive to health effects of air pollution, which is reflected in the activity guidelines issued by the EPA and others. However, they may also experience larger benefits from park visits, which would influence the defensive behaviors adopted by their caregivers.

The results for playground visits are more sensitive to the specification used, particularly the level of the spatial fixed effects (Table 2b). This is likely to be because the average daily number of observed devices within playground boundaries is lower than within park boundaries. In general, playground visits are significantly lower on days with air pollution, relative to the base rate on days with Good air quality, although specifications with state or county fixed effects do not show consecutive reductions in visitation with each increasingly polluted category of air quality.

In our preferred specification (model (4) and Figure 4b), the pattern of visits to playgrounds is broadly similar to the pattern for parks in that there is a small, but statistically significant, decrease in visits on days with Moderate air quality to 0.95 times the base rate on days with Good air quality. The reduction in visits between days with Moderate air quality and days with Unhealthy for Sensitive Groups air quality (to 0.93 times the base rate) is not statistically significant. We see larger reductions in playground visits as air quality deteriorates to Unhealthy, with only 0.6 times the number of observed devices relative to Good days; and further reductions on Very Unhealthy/Hazardous days to 0.5 times the base visitation rate.

Comparing the park and playground results, we see a slightly smaller reduction in playground visits than park visits at lower levels of air pollution (Moderate or Unhealthy for Sensitive Groups), but a larger reduction in playground visits than park visits in the most severe categories of air pollution. However, the fairly large standard errors on playground visits mean that these differences are not statistically significant.

4.3 Heterogeneous responses to air pollution

In addition to the average effects of air pollution on park visits, we estimate how these effects vary by neighborhood characteristics, city size, and previous air quality.

Neighborhood characteristics represent weighted averages of all neighborhoods from which people visit a given park. Education is measured as the share of the population with more than some college education, and income is measured as the share of the population with an income greater than $75,000/year. The results for neighborhood education and neighborhood income levels are similar as these variables are highly correlated. The most notable finding is that in parks visited by people from neighborhoods with high average levels of education or income, there is a large reduction in visits as soon as air quality declines from Good to Moderate. Visits to these parks then stay fairly constant as air quality deteriorates further (Figure 5a and b). In contrast, no significant reduction in visits is observed to parks where most visitors come from neighborhoods with medium or low levels of education or income when air quality is Moderate or Unhealthy for Sensitive Groups. There is some reduction in visits to parks used by residents of middle-education or low-income neighborhoods when air quality is Unhealthy. When air quality is Very Unhealthy or Hazardous, visits are reduced by a similar amount in all neighborhood types, including high income and high education neighborhoods. Taken together, these results suggest that when air pollution is severe, everyone changes behavior in similar ways. However, individuals from neighborhoods with higher levels of education or income begin to respond at much lower levels of pollution.

We disaggregate the effects by the size of the city in which the park is located, where large cities have populations of more than 250,000, medium cities have 100,000 - 250,000 people, and small cities have fewer than 100,000 people (Fig 5c). The change in park visits at Moderate levels of air pollution are small in magnitude, and similar across all city sizes. We see incrementally greater reductions in park visits as air quality worsens in all city sizes. However, the reductions are greater for large cities, particularly at Unhealthy, Very Unhealthy and Hazardous levels of $PM_{2.5}$.

Finally, we compare responses to different levels of air pollution when the prior day was worse than Moderate with responses when the prior day was Good or Moderate. We consistently see greater reductions in park visits if air quality was poor the previous day, although these differences only become statistically significant as pollution on the current day becomes severe. Ideally we would estimate the effects of each level of prior air pollution of different durations prior to the 'current' day. However, we do not have sufficient numbers of days with worse than Moderate air pollution averaged over 24 hours to precisely identify these effects. Broadly, these results indicate that the response may increase rather decrease over time, possibly because people are more likely to adjust their plans if they are primed for the likelihood of a polluted day.

4.4 Robustness to alternative samples and specifications

One limitation of this analysis is that the main independent variable, $PM_{2.5}$ potentially represents air pollution from a range of sources, while we are primarily interested in how people respond to pollution from wildfire smoke. We therefore estimate the effect of $PM_{2.5}$ on park visits with the largest cities of Seattle and Portland excluded from the sample. While all days in our study period are recorded as Good in these cities during the month of June (when substantial fire activity had not yet begun), people in larger cities are more likely to be subject to pollution from transportation and industrial sources. We find that the results with large cities excluded (Table 3, column 2) show a similar overall pattern to the results from the base model with all cities included (Table 3, column 1). However, the responses at each level of air pollution are slightly smaller in the restricted sample than in the full sample. This accords with Figure 5c, showing the differences in responses by city size, indicating that the differences are likely to be due to different populations rather than different sources of air pollution.

We estimate responses to air pollution with the 10% of parks with the highest levels of visitation and the 10% of parks with the lowest levels of visitation (Table 3, columns 3 and 4), to determine if either of these park types is strongly influencing the results. Parks with particularly high or low visitation may differ from others in the sample in unobservable ways, and may be more subject to idiosyncratic influences on visitor numbers. For example, heavily-visited parks may be more likely to hold sports or cultural events that draw large numbers on particular days. Alternatively, a little-visited park would be subject to a large proportional increase in visits from a single group. The results with low-visit parks excluded are almost identical to the base results with the full sample. When high-visit parks are excluded, we no longer observe a statistically significant response when air quality is Moderate or Unhealthy for Sensitive Groups. The response to pollution levels that are Unhealthy or Very Unhealthy/Hazardous is similar to the response within the full sample.

As temperature and air quality are likely to be correlated, and both will influence outdoor activity, we re-estimate the base model with a more flexible functional form for temperature to allow for nonlinearities beyond the quadratic relationship (Table 3, column 5). We include temperature in 5 degree Fahrenheit bins. The influence of air quality on park visits is almost identical to the base model. The coefficients on the temperature bins show increases in park use from 46 degrees to 105 degrees, with visits decreasing on days with maximum temperatures of more than 105 degrees. It is likely that people time their visits for periods during the day when temperatures are below their maximum, although we do not capture this with daily data. We also re-estimate the model using PRISM gridded weather data, which avoids the issue of missing weather station data and allows for inclusion of vapor pressure deficit as a measure of humidity (Table 3, column 6). We find that park visitation is slightly higher when air quality is Moderate to Unhealthy and slightly lower when air quality is Very Unhealthy or worse. However the results are substantively the same.

We estimate the model using a continuous rather than categorical measure of $PM_{2.5}$, and estimating the marginal effects at the thresholds for each AQI category. Continuous $PM_{2.5}$ is included in quadratic form, to allow for nonlinear responses. The estimated effects of air pollution on park visits are similar in this specification (Table 3, column 7), when compared with the base model using categorical AQI (Table 3, column 1). Finally, we compare the results from the Poisson specification with those from a Linear Probability model. Table 4 shows the coefficients from the latter, along with the implied proportions of observed devices when air quality is poor relative to the baseline numbers of devices when air quality is "Good". We use the mean number of observed devices for this comparison with the Incidence Rate Ratios from the Poisson models. We find that the results are extremely similar across the two models.

5. Conclusions

Wildfire smoke is an increasingly dominant source of air pollution, with severe consequences for human health (Abdo et al. 2019; Aguilera et al. 2021; Liu et al. 2017; Moeltner et al. 2013; Xu et al. 2020). The main drivers of these wildfire trends are historic fire management approaches that have led to high current fuel loads in forested areas, and the warmer, drier conditions associated with global climate change (Burke et al. 2021). These influences will take many decades or longer to reverse, so the main opportunities for mitigating negative health effects involve minimizing exposure through changes in behavior or infrastructure. One key recommendation for reducing pollution exposures during wildfire season is to limit time and physical activity outdoors. There is evidence that people reduce outdoor activities in response to urban air pollution or pollution alerts (e.g. Graff Zivin and Neidell 2009; Ward and Beatty 2016; Yoo 2021).

However, less is known about how people respond to air pollution during wildfire events, particularly in less urban settings. In the United States, $PM_{2.5}$ associated with wildfire smoke reaches much higher levels than $PM_{2.5}$ associated with urban and industrial pollution. In the Northwest United States, smoke is also limited to the summer season, when people may be on vacation and are planning to spend time outdoors. These differences are likely to affect the type and degree of behavioral response.

Our indicator of outdoor activity is the number of mobile devices observed within the boundaries of parks or playgrounds. While these do not tell us exactly how many people visited a given park or playground, they provide a measure of variation in visitation on days with poor air quality relative to days with good air quality. Overall, we see reductions in park and playground visits as air quality deteriorates. On days categorized as Moderate or Unhealthy for Sensitive Groups, significantly fewer visits are observed within park and playground boundaries, although the effect is not large, with visits falling to 90-94% of the number of visits observed on Good days in parks, and 93-95% of the baseline in playgrounds. EPA guidelines encourage outdoor activity on Moderate days for everyone except those who are unusually sensitive to air pollution, who may wish to avoid prolonged exertion. Similarly, guidelines for days that are Unhealthy for Sensitive Groups suggest that members of sensitive groups, such as people with heart or lung disease, older adults, children and teenagers, should reduce exertion but not avoid going outside altogether. A small reduction in outdoor activity is consistent with these recommendations.

Our results show significantly larger reductions in park and playground visits on days categorized as Unhealthy to less than 80% of baseline visits in parks, and 60% of baseline visits in playgrounds. On these days, members of sensitive groups are recommended to consider moving activities indoors, while others are recommended only to reduce outdoor exertion. Park visits fall still further on days classed as Very Unhealthy or Hazardous days, to 60% of baseline in parks and 50% of baseline in playgrounds. Guidelines for Very Unhealthy days suggest that sensitive groups avoid all physical activity outdoors and everyone considers moving activities indoors, and guidelines for Hazardous days are that everyone remains indoors.

One limitation of this analysis is that we do not observe all visits to parks and playgrounds, but rather the number of mobile devices. We therefore express all results in terms of the relative number of devices observed on days with poor air quality relative to days with Good air quality. To interpret this as reflecting variation in the number of visits, we must assume that the approximately 30% of people with mobile devices that report information to the Near Vista platform change their behavior in similar ways to park visitors that are not recorded. Analysis conducted by Near suggests that while the sample is largely representative of the US population, older adults and those who did not finish high school are slightly underrepresented. We would expect older adults to be more responsive to air pollution due to greater sensitivity to negative health effects. Conversely, our heterogeneity analysis shows that those with lower education are less responsive to moderate levels of air pollution than those with higher levels of education. Therefore these effects will to some degree offset each other. Beyond the question of representativeness among adults, we are unlikely to observe young children in the dataset because they typically do not carry mobile devices. We address this by separately estimating changes in visits for parks and playgrounds, as the latter are more likely to be used by caregivers of young children.

A second limitation is that we do not observe adjustments to length of time for park or playground use within a given day for those who perhaps reduce exposure to air pollution but do not forgo visits altogether. Our air quality measures are based on 24hr averages, although the level of pollution is likely to vary during the day. Therefore, even on a day where the average level of $PM_{2.5}$ is high, there may be a period where it is relatively better and some people may time their outdoor activity for that period. Alternatively, people may avoid park visits during a bad period of a relatively clear day. Also, we only observe whether someone enters a park or playground, and not how long they spend there or what they do. We expect that some of those who continue using parks and playgrounds reduce the amount of time they spend, reduce their level of exertion, or both as air quality deteriorates. Our results therefore indicate a lower bound on overall changes in outdoor activity.

Given that the estimated changes in park use represent a lower bound on behavioral response to air pollution during wildfire season, it is notable that our results indicate substantial changes in behavior, particularly when air quality becomes very poor. This could be in direct response to health guidelines, and reflect awareness of the health effects of smoke exposure. It may also be because people find it unpleasant to be outside or because outdoor events such as sports competitions or social gatherings are cancelled. While we observe a large response to poor air quality, our results also show that many people continue to visit parks and playgrounds, even when there are significant negative health consequences from doing so. A potential explanation for this is that for some individuals, the costs of forgoing park visits are high relative to the actual or perceived benefits.

Estimates of willingness to pay to avoid morbidity effects of wildfire smoke are fairly similar, regardless of methods used: Richardson et al. (2013) estimate willingness to pay to avoid one symptom day at US$114[1] using defensive behavior methods, and US$125 using contingent valuation methods. Jones et al. (2016) estimate a value of US$162 per symptom day based on defensive use of air filters, and Jones (2016) estimates the value of avoided symptoms at US$157/day using life satisfaction methods. These estimates

[1] All values in this section have been converted to 2023 US $

are higher than values based on cost of illness because they include symptoms that do not necessarily lead to treatment, but they are considerably lower than estimated mortality costs associated with smoke exposure (Dittrich and McCallum 2020).

Although there are health benefits from reducing park use when $PM_{2.5}$ levels are high, there are also substantial costs associated with doing so. Costs of avoiding outdoor activities or benefits from engaging in outdoor activities have been estimated using stated preference surveys. For example, Mansfield et al. (2006) estimate parents' marginal willingness to pay to avoid a 1-day restriction on outdoor activity for their child at US$52. Rosenberger et al. (2017) review multiple studies, and estimate the consumer surplus associated with outdoor recreation activities such as picnicking, relaxing in nature, and hiking, walking or running at US$40-100 per activity. There may also be physical or mental health costs from reductions in exercise and time in nature. Zhang et al. (2022) find that an additional 30 minutes/week of greenspace activity significantly reduces observed and self-reported measures of physical and mental health, and Barton and Pretty (2010) find the greatest marginal effect of physical activity in greenspace on mood and self-esteem results from the first 5 minutes. This suggests that there are likely to be important health consequences from avoiding parks altogether. In addition, since parks and playgrounds are typically free to visit, additional costs may be incurred if replacement activities require entrance fees or other expenditure, for example indoor swimming pools, cinemas, cafes or shopping malls.

As well as estimating average changes in park use, we also examine heterogeneity in changes in visits to parks vs playgrounds, and by neighborhood type. There is evidence that the health consequences of exposure to wildfire smoke can be greater in low socio-economic status neighborhoods relative to high socio-economic status neighborhoods (Rappold et al. 2012; Reid et al. 2023). This is despite similar wildfire smoke exposures by neighborhood type (Heft-Neal et al. 2022). One explanation for observed disparities in health impacts is that there are pre-existing differences in risk factors that determine susceptibility to negative health effects or in access to healthcare (Reid et al. 2023). Our results highlight the additional role of variation in adoption of defensive behaviors as a contributor to disparities in health impacts of wildfire smoke. Understanding the extent to which this variation reflects differences in the benefits and costs of avoiding park use can inform policy interventions to mitigate the overall effects of wildfire smoke exposure.

The first type of heterogeneity we consider is use of parks compared with playgrounds. We estimate results separately for these locations because playgrounds are likely to have a larger share of children, a sensitive group, than parks as a whole. In playgrounds, we see a slightly smaller reduction in visits on Moderate or Unhealthy for Sensitive Groups days, relative to baseline, but a larger response on Unhealthy and Very Unhealthy/Hazardous days. This larger response to high levels of pollution in places visited by young children, who are a more sensitive group, suggests that caregivers of these children are aware that it is particularly important for them to avoid outdoor activity when air pollution is bad. In other words, the perceived benefits of avoiding exposure are high. However, the more limited response on Moderate and Unhealthy for Sensitive Groups days in playgrounds relative to parks suggests that the costs of remaining indoors may also be relatively high for young children and their caregivers compared with the general population.

The second source of heterogeneity we consider is among parks that serve neighborhoods with different economic and demographic characteristics. One potential reason for the smaller response to moderately severe levels of air pollution in neighborhoods with low and medium levels of income and education compared with neighborhoods with high levels of income and education is differences in knowledge of the health impacts of pollution or access to information about air quality on a given day. However, previous research suggests that although individuals with more education have more knowledge about health effects of air pollution, the size of the effect is not large (Del Ponte et al. 2022), and searches for air quality information do not differ by income level (Burke et al. 2022).

An alternative explanation is that the differential responses are driven by differences in benefits or costs of avoiding outdoor activity. The benefits of staying indoors are a function of the degree to which indoor air quality is better than outdoor air quality. This will depend on the inherent characteristics of housing structures and behavioral choices such as keeping windows and doors closed. Burke et al. (2022) find that structural factors result in higher infiltration in low-income neighborhoods, but these effects are largely offset by behavioral actions within the home which do not vary with income. Benefits of avoiding park use also depend on pre-existing health conditions such as asthma, which is more prevalent among disadvantaged socio-demographic groups (Gold and Wright 2005). If differences in benefits of avoiding park use were primarily driven by differences in the health risks of wildfire smoke exposure, we would therefore expect earlier responses to air pollution in lower socio-economic status neighborhoods. This suggests that the costs of avoiding park use may be more important drivers of the observed difference in responses than the relative health benefits of doing so: lower-income households are likely to have more limited willingness or ability to pay entrance fees for alternative indoor locations such as indoor swimming pools, gyms, activity centers or movie theaters. At the same time, the non-monetary costs of staying at home will be higher for those with smaller living spaces or fewer options for indoor entertainment.

To the extent that lower responsiveness in less advantaged neighborhoods could be a rational response to differences in costs and benefits of avoiding park use (as opposed to solely based on differences in information), there are two key policy implications. The first is that we would expect to observe larger health impacts from similar levels of wildfire smoke exposure, requiring additional resources and support for identification and treatment of health outcomes such as respiratory conditions (Liu et al. 2017; Reid et al. 2019), cardiovascular illness (Liu et al. 2017; Delfino et al. 2009) and pregnancy complications (Abdo et al. 2019; Holstius et al. 2012). Whether socio-economic differences in park use on polluted days are driven by lower benefits due to poor indoor air quality, or higher costs related to alternative activities, the second main policy implication is that provision of publicly accessible clean-air spaces such as libraries or community centers is likely to be important for reducing health disparities resulting from differential behavioral responses to wildfire smoke.

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Tables

Table 1. Descriptive Statistics for polygons representing parks and playgrounds (N = 108,092)

Statistic	Mean	St. Dev.	Min	Max
Observed Devices	17.9	50.1	0	911
Parks only	28.2	59.9	0	911
Playgrounds only	7.55	34.9	0	911
Particulate Matter (μg/m^3)	13.7	31.8	0.881	436
Max Temp (F°)	80.3	10.4	46	116
Precipitation (in.)	0.038	0.141	0.000	2.19

Table 2a. Incidence rate ratio of observed mobile devices within park boundaries for daily categories of $PM_{2.5}$ Air Quality Index (AQI)

	Park Visitation			
	(1)	(2)	(3)	(4)
Good (baseline)	1.00	1.00	1.00	1.00
	-	-	-	-
Moderate	0.889***	0.916***	0.916***	0.938***
	(0.0270)	(0.0218)	(0.0200)	(0.0166)
Unhealthy for Sensitive Groups	0.905***	0.889***	0.882***	0.899***
	(0.0346)	(0.0281)	(0.0262)	(0.0288)
Unhealthy	0.745***	0.753***	0.769***	0.782***
	(0.0428)	(0.0289)	(0.0308)	(0.0306)
Very Unhealthy/Hazardous	0.647***	0.634***	0.618***	0.617***
	(0.0467)	(0.0372)	(0.0333)	(0.0317)
Park FE	No	No	Yes	Yes
County FE	No	Yes	No	No
State FE	Yes	No	No	No
Year, month, day-of-week FE	Yes	Yes	Yes	No
State x year and state x month FE	No	No	No	Yes
Month x day-of-week FE	No	No	No	Yes
Weather and COVID-19 Restrictions	Yes	Yes	Yes	Yes
Observations	108092	108092	108092	108092
Pseudo R2	0.0211	0.104	0.825	0.827
Wald Chi2	114.9	147.2	180.1	196.0

Notes: Incidence rate ratios (i.e. exponentiated coefficients) from fixed-effects Poisson regression model, with standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, where the null hypothesis is IRR = 1. Incidence rate ratios are calculated relative to baseline of Good air quality. The model specifications in columns (1), (2) and (3) include state, county and park fixed effects, respectively, with year, month and day-of-week fixed effects in all cases. Model (4) includes park fixed effects, with state-specific year and month fixed effects and month-specific day-of-week fixed effects. All specifications include temperature and precipitation in quadratic form, and binary indicators of whether a Covid-19 stay-at-home order was in place on a given day. Standard errors are clustered at the park level.

Table 2b. Incidence rate ratio of observed mobile devices within playground boundaries for daily categories of $PM_{2.5}$ Air Quality Index (AQI)

	Playground visitation			
	(1)	(2)	(3)	(4)
Good (baseline)	1.00	1.00	1.00	1.00
	-	-	-	-
Moderate	0.720^{***}	0.905^{***}	0.917^{***}	0.953^{***}
	(0.0430)	(0.0274)	(0.0212)	(0.0172)
Unhealthy for Sensitive Groups	0.999	0.914^{*}	0.899^{***}	0.931^{***}
	(0.0609)	(0.0438)	(0.0214)	(0.0241)
Unhealthy	0.281^{***}	0.566^{***}	0.579^{***}	0.602^{***}
	(0.0502)	(0.0548)	(0.0514)	(0.0469)
Very Unhealthy/Hazardous	0.438^{***}	0.488^{***}	0.482^{***}	0.498^{***}
	(0.0405)	(0.0457)	(0.0470)	(0.0451)
Playground FE	No	No	Yes	Yes
County FE	No	Yes	No	No
State FE	Yes	No	No	No
Year, month, day-of-week FE	Yes	Yes	Yes	No
State x year and state x month FE	No	No	No	Yes
Month X day-of-week FE	No	No	No	Yes
Weather and COVID-19 Restrictions	Yes	Yes	Yes	Yes
Observations	106970	106970	106970	106970
Pseudo R2	0.344	0.488	0.844	0.848
Wald Chi2	320.0	152.4	260.7	293.3

Notes: Incidence rate ratios (i.e. exponentiated coefficients) from fixed-effects Poisson regression model, with standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, where the null hypothesis is IRR = 1. Incidence rate ratios are calculated relative to baseline of Good air quality. The model specifications in columns (1), (2) and (3) include state, county and playground fixed effects, respectively, with year, month and day-of-week fixed effects in all cases. Model (4) includes playground fixed effects, with state-specific year and month fixed effects and month-specific day-of-week fixed effects. All specifications include temperature and precipitation in quadratic form, and binary indicators of whether a Covid-19 stay-at-home order was in place on a given day. Standard errors are clustered at the playground level.

Table 3. Robustness to alternative specifications (Parks)

	(1) Base model	(2) Excluding large cities	(3) Excluding low-visit parks	(4) Excluding high-visit parks	(5) Flexible temperature specification (5° F bins)	(6) Gridded weather (incl. vapor pressure deficit)	(7) Continuous $PM_{2.5}$ (marginal effects at AQI cutoffs)
Moderate	0.938***	0.960*	0.938***	0.997	0.937***	0.944***	0.920***
	(0.0166)	(0.0233)	(0.0166)	(0.00833)	(0.0166)	(0.0158)	(0.012)
Unhealthy for Sensitive Groups	0.899***	0.935	0.899***	0.995	0.900***	0.926***	0.860***
	(0.0288)	(0.0382)	(0.0288)	(0.0122)	(0.0290)	(0.0271)	(0.019)
Unhealthy	0.782***	0.857***	0.783***	0.833***	0.779***	0.790***	0.674***
	(0.0306)	(0.0315)	(0.0306)	(0.0177)	(0.0298)	(0.0297)	(0.031)
Very Unhealthy/Hazardous	0.617***	0.703***	0.620***	0.644***	0.616***	0.594***	0.595***
	(0.0317)	(0.0327)	(0.0318)	(0.0172)	(0.0313)	(0.0316)	(0.029)
Park FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	No	No	No	No
State FE	No	No	No	No	No	No	No
Year, month, day-of-week FE	No	No	No	No	No	No	No
State x year and state x month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather and COVID-19 Restrictions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	108092	59780	101369	98299	108092	108092	108092
Pseudo R2	0.827	0.821	0.820	0.641	0.827	0.826	0.827
Wald Chi2	196.0	119.4	194.1	409.9	321.5	144.8	207.2

Notes: Incidence rate ratios (i.e. exponentiated coefficients) from fixed-effects Poisson regression model, with standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, where the null hypothesis is IRR = 1. Incidence rate ratios are calculated relative to baseline of Good air quality. All specifications include temperature, precipitation and binary indicators of whether a Covid-19 stay-at-home order was in place on a given day. Temperature and precipitation are included in quadratic form with the exception of Column 5 in which temperature is included in bins of 5 degrees Fahrenheit. Standard errors are clustered at the park level. The results in Column 6 show the marginal effects of $PM_{2.5}$ at the AQI cutoffs for Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy and Very Unhealthy, based on estimation of park visits as a function of a quadratic of continuous $PM_{2.5}$.

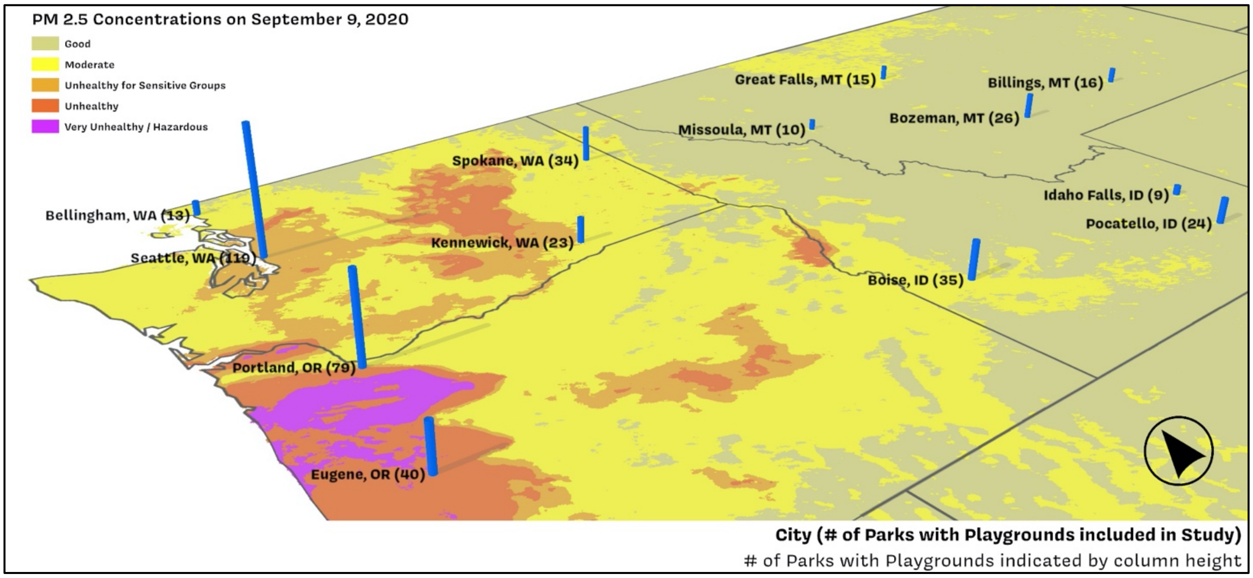
Table 4: Comparison of linear probability model with Poisson specification

	(1) Base model (Poisson)	(2) Coefficients from Linear Probability Model	(3) Proportion of visits relative to baseline of "Good" AQI (using mean visits = 28.37)
Moderate	0.938***	-1.743***	0.939
	(0.0166)	(0.539)	
Unhealthy for Sensitive Groups	0.899***	-2.780***	0.902
	(0.0288)	(0.906)	
Unhealthy	0.782***	-5.967***	0.790
	(0.0306)	(1.025)	
Very Unhealthy/Hazardous	0.617***	-9.590***	0.662
	(0.0317)	(1.014)	
Observations	108092	108092	

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (2) shows the coefficients on each AQI category from a linear probability model with Observed Devices as the dependent variable. We calculate the implied proportion of visits relative to baseline visits to each park on "Good" days for comparison with the incidence rate ratios from the Poisson specification, and display these in Column (3)

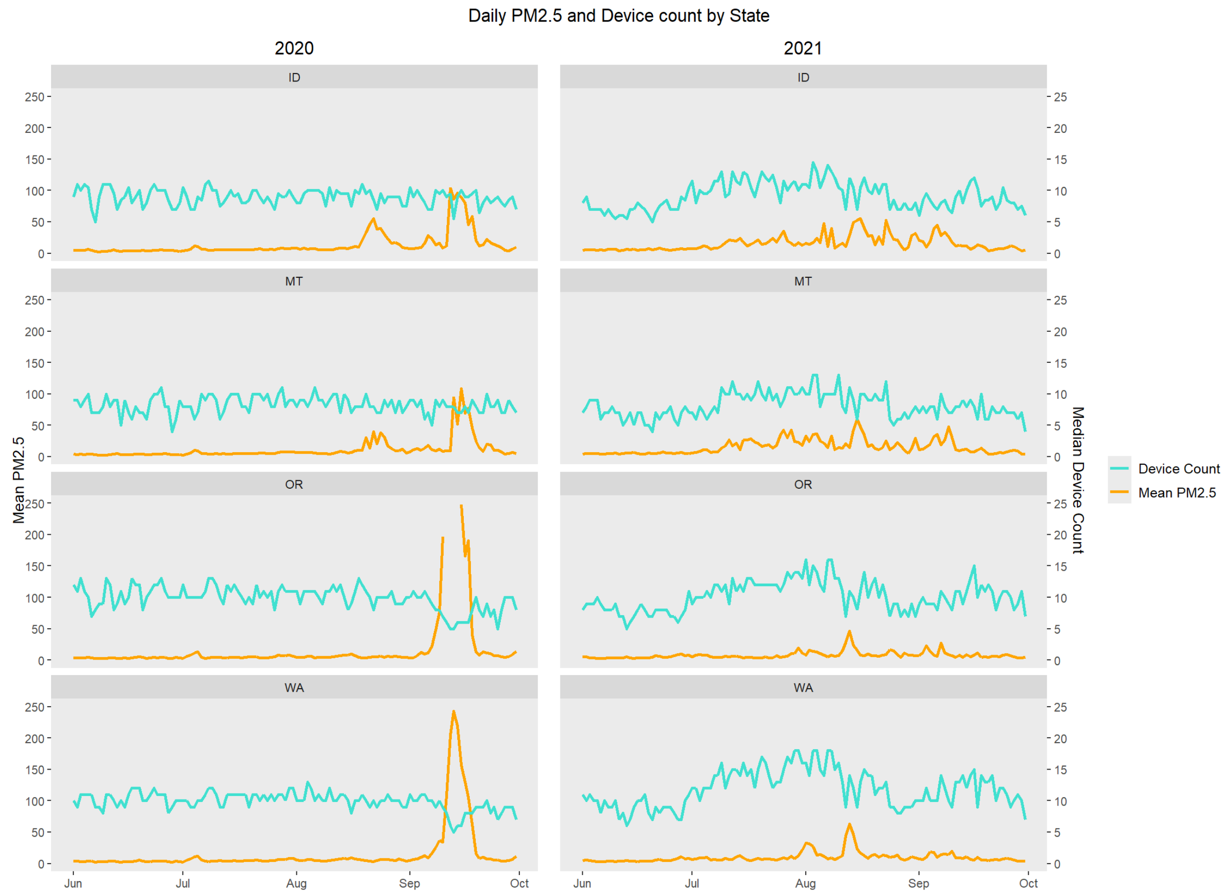
Figures

Figure 1. PM 2.5 Concentrations on September 9, 2020



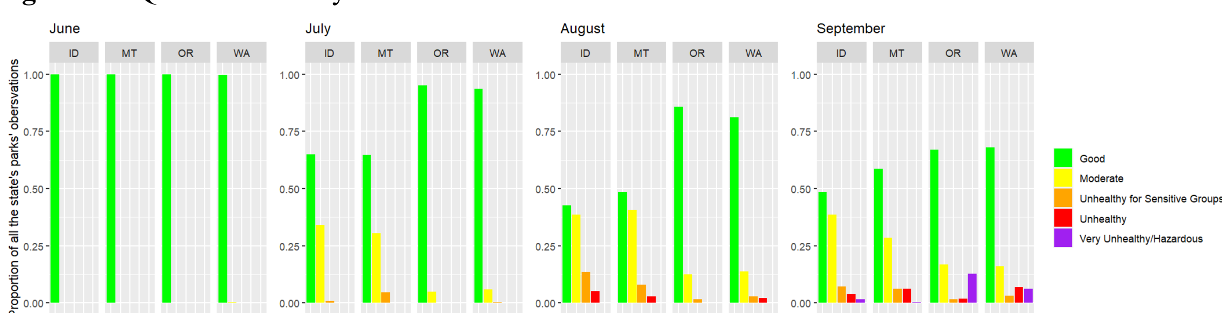
Notes: This map includes the thirteen cities selected for this study, including the number of parks with playgrounds (as found in the ParkServe® database) within each of the selected cities. The number of parks and playgrounds included in the study are equal, as each playground corresponds to the park in which it is situated. In an attempt to show the variability in air quality common in this region, PM 2.5 concentrations from September 9, 2020 are displayed as an example of the daily 1-km resolution maps of surface fine particulate matter used in this study.

Figure 2. Device count and PM2.5 by state and week-of-year



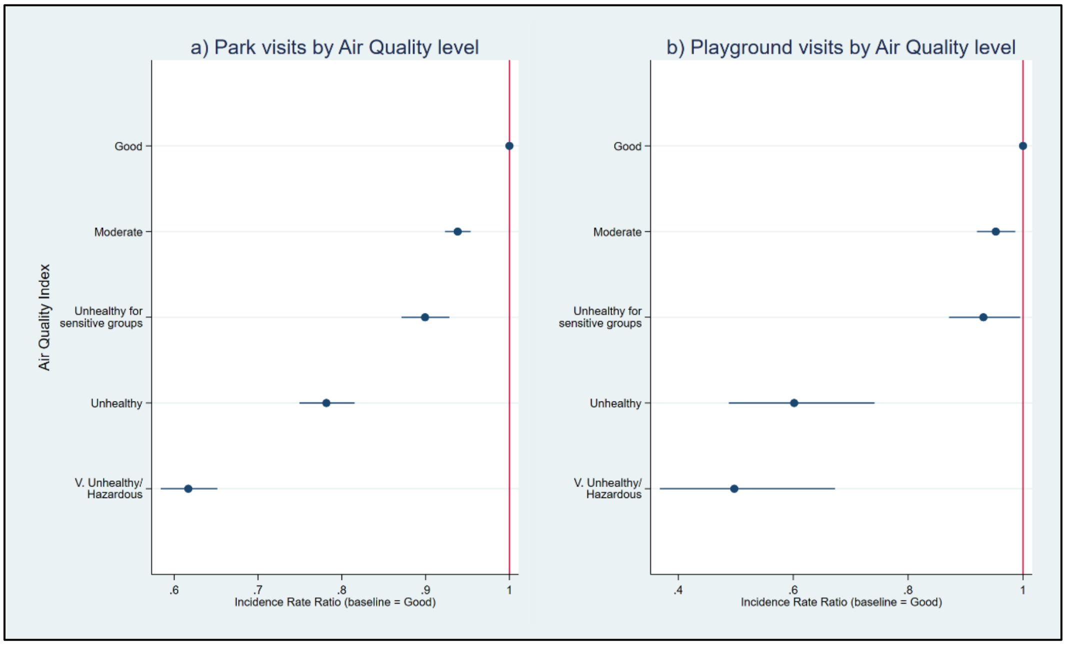
Notes: Median device counts and mean AQI are measured within the spatial boundaries of polygons representing individual parks. The panels show daily values by state and year for Idaho (ID), Montana (MT), Oregon (OR) and Washington (WA).

Figure 3. AQI distribution by month and state



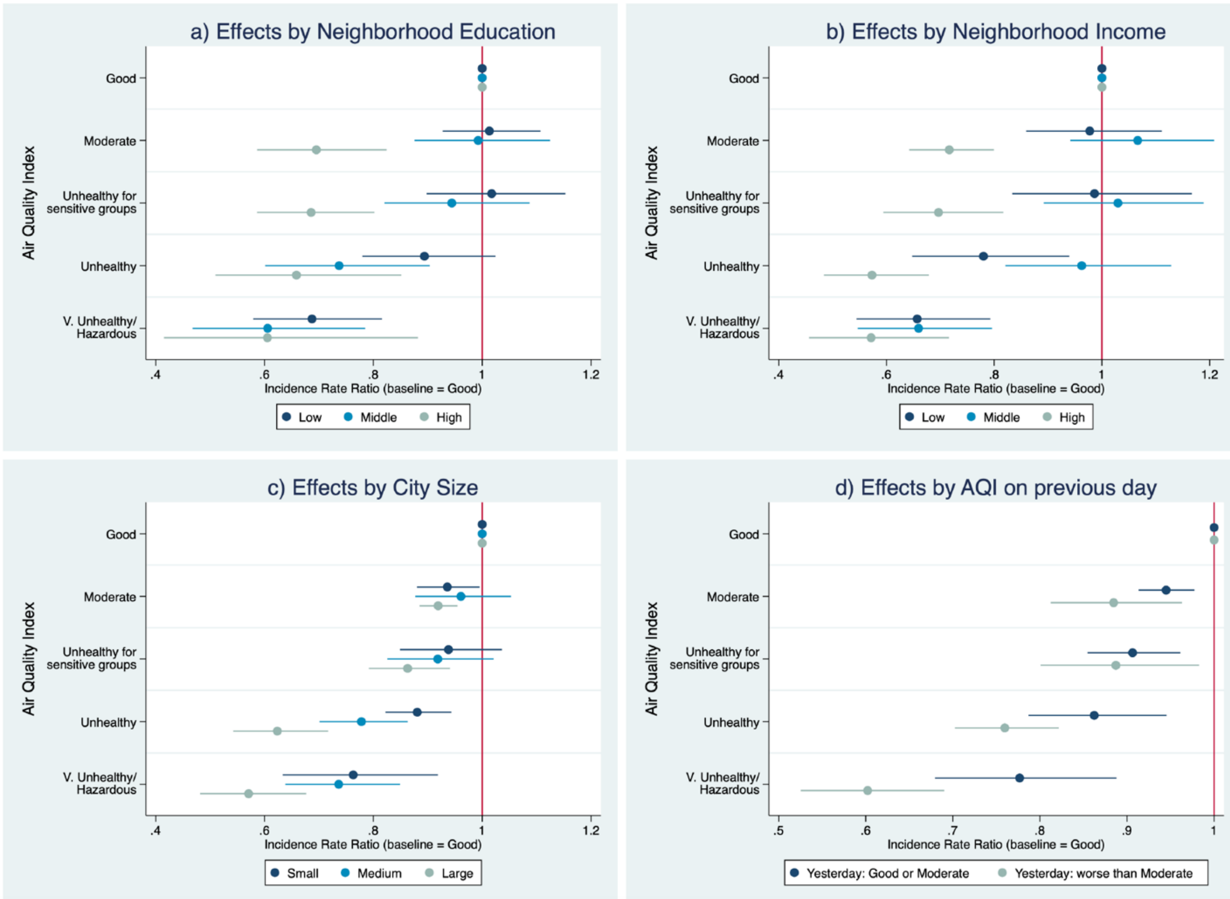
Notes: Each bar shows the proportion of days within a given state and month that fall in each AQI category based on 24hr $PM_{2.5}$ concentrations.

Figure 4. Impacts of air pollution on observed devices within boundaries of a) Parks and b) Playgrounds



Notes: Incidence rate ratio of visits to parks (a) and playgrounds (b) on days when the 24hr mean concentration of $PM_{2.5}$ falls with each AQI category. Poisson regression models with park/playground, state-by-month, state-by-year, and month-by-day or week fixed effects and time variant controls for temperature, precipitation and Covid-19 stay-at-home orders.

Figure 5. Heterogeneous effects of air pollution on park visits



Notes: Incidence rate ratio of visits to parks on days when the 24hr mean concentration of $PM_{2.5}$ falls with each AQI category. Poisson regression models with park/playground, state-by-month, state-by-year, and month-by-day or week fixed effects and time variant controls for temperature, precipitation and Covid-19 stay-at-home orders. Results are disaggregated using weighted averages of education (a) and income (b) in the neighborhoods representing the "common evening location" of visitors to each park; by the size of the city in which the park is located (c) where Small cities have fewer than 100,000 residents, Midsize cities have 100,000-250,000 residents, and Large cities have more than 250,000 residents; or by whether the AQI was rated higher than Moderate the previous day, based on the 24hr mean concentration of $PM_{2.5}$ (d).