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Increased medical and emergency department claims for asthma following wildfire smoke exposure in Washington state, 2014-2018.

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Summary

Health impacts from wildfire smoke are likely to become a growing public health concern in Washington state. We examined the short-term impact of wildfire smoke exposure on health care utilization for asthma from 2014-2018 using medical claims data from the Washington All-Payer Claims Database, and wildfire smoke data provided by the Washington State Department of Ecology. A 10 µg / m3 one-day increase in fine particulate matter from wildfire smoke was associated with a 3% increase in medical claims for asthma for the 10 days following exposure, and a 2% increase in emergency department claims on the day of exposure, with higher odds at higher exposure. Over 5 fire seasons from 2014 through 2018, increased healthcare utilization for asthma associated with the immediate effect of wildfire smoke cost $4.5 million. This analysis considers only the immediate increase in utilization for asthma within two weeks of an exposure event. In addition, a yearly fire season compounds the long-term impact of chronic conditions, which would lead to higher morbidity and cost.

Background

Health impacts from wildfire smoke will likely become a growing public health concern in Washington state. Wildfires in the western United States are projected to become more frequent and more severe as a result of human-caused climate change [1]. In addition to smoke from wildfires, smoke from prescribed burns intended to prevent wildfires may also increase.

Adverse health effects from poor air quality are well documented. Air pollution is associated with increased morbidity and mortality for respiratory and cardiovascular diseases [2] [3], as well as lung cancer [4], low birth weight [5], and all-cause mortality [6] [7]. Smoke from wildfires contains many of the same components as urban air pollution, with similar health impacts [7] [8] [9]. In particular, wildfire smoke produces large amounts of fine particulate matter ($PM_{2.5}$), defined by a particle size less than 2.5 µm in diameter, which are able to penetrate deep into the lungs [10]. Wildfire smoke may be especially harmful to children with respiratory conditions such as asthma [11].

Estimating individual smoke exposure and associated health effects is difficult. PM2.5 monitors are sparsely distributed in some parts of Washington. Depending on topography and wind conditions, the nearest monitor may not be the most representative of ambient conditions. Satellite data, meteorology data and chemical transport models have been used to improve exposure estimates between stations [12] [13] [14]. Individual behavior can also greatly affect exposure. A person spending most of their time indoors will experience much different exposure than a person working outdoors, and indoor air quality can vary greatly, depending on many factors [15]. Furthermore, studies of air pollution typically assign exposure based on residential location. However, people with high mobility may encounter quite different conditions [16]. Finally, the timing of exposure is important. For some health conditions, a single smoke event may have immediate impact, while for others, effects may be delayed, or depend on cumulative exposure over a season, or over many years [17].

Recent studies examined health impacts of wildfire smoke events in Washington state, and addressed the problem of estimating exposure. Gan et. al. [13] examined hospital admissions during the 2012 wildfire season. They found that a 10 $\mu g/m^3$ increase in daily average smoke $PM_{2.5}$ was associated with an 8% increase in asthma hospitalizations. The association between smoke $PM_{2.5}$ and for chronic obstructive pulmonary disease (COPD) hospitalizations ranged from no effect to 8% increase, depending on the method used to estimate smoke exposure. Doubleday et. al. [7] found that, from 2006-2017, the odds of non-traumatic mortality increased 1% on days with smoke exposure, and 2% the day after exposure. The odds of same-day mortality from respiratory illness increased 9%, and the odds of same-day mortality from COPD increased by 14%.

This study examined time dependent associations between wildfire smoke $PM_{2.5}$ exposure and healthcare utilization for asthma from 2014-2018 using medical and emergency department claims data from the Washington All-Payer Claims Database (WA-APCD) [18]. We defined smoke exposure using a variation of the method of Doubleday et. al. [7]. We used a distributed lag time series model to assess associations with a time lag of up to 14 days.

Study population

The study population included Washington residents with uninterrupted medical insurance and at least one medical claim for asthma during the June to September fire season for 2014, 2015, 2016, 2017, or 2018. The WA-APCD includes medical, dental and pharmacy claims from publicly funded payers. This includes Medicaid, Medicare Advantage, Public Employees Benefit Board, and Labor and Industries, subsidized commercial plans (including group and individual markets), and all pharmacy claims. WA-APCD does not include claims from the Veterans Administration or self-funded commercial plans. Medicare fee-for-service data is only available for 2015 through 2017.

Smoke Exposure

Daily $PM_{2.5}$ smoke exposure data by zip-code in Washington state for 2014-2018 were provided by the Washington State Department of Ecology [*Personal communication from Matt Kadlec, Washington Dept. of Ecology, April 12, 2021*]. Washington State University provides daily forecasts of $PM_{2.5}$ concentration for the Pacific Northwest through its Air Indicator Report for Public Awareness and Community Tracking (AIRPACT-4) [18]. Doubleday et. al. [7] applied AIRPACT forecasts to determine the most representative air quality monitor on any given day at any given location in Washington. Daily air quality, including $PM_{2.5}$ for air quality monitoring stations in Washington are available from the United States Environmental Protection Agency [19]. PM.5 monitors were operated by Washington air quality authorities in 70 different places for at least parts of the June-through-September fire seasons from 2014 through 2018 [7]. 77% of the locations had data more than half of the 610-day total span of these seasons. Over five wildfire seasons from 2014-2018, the study population experienced wildfire smoke on 10% of person-days (Table 1).

Table 1. Distribution of smoke exposed person-days in the study population.

Smoke $PM_{2.5}$ ($\mu g / m^3$)	Person-days	Percent
0-9	205,911	0.4
10-19	2,206,015	4.2
20-29	967,138	1.8
30-39	686,715	1.3
40-49	445,683	0.8
50-59	273,657	0.5
60-69	156,014	0.3
70+	449,793	0.8
No Smoke	47,634,785	89.8

Analysis

We used a distributed-lag nonlinear model (DLNM) to test if healthcare utilization among asthma patients was associated with wildfire smoke up to 14 days following exposure. DLNM fits a statistical regression model (in this case logistic regression) with the effect distributed across a range of time lags. The regression model determines the odds ratios at each point of a user-defined exposure function. We modeled the effect to be linear with respect to $PM_{2.5}$ concentration, and we modeled the effect with respect to time lag to be piecewise constant with breaks at lag 1,2,3,5,8, and 11.

To model health care utilization, we used a variation of the case-control study design where the primary unit of analysis was person-days. For each year, 2014-2018, we identified susceptible WA-APCD members with at least one claim for asthma in the year and continuous medical insurance coverage through the June-September fire season. Each eligible member would then have 122 associated person-days in the fire season. We defined a utilization case as a person day with a medical claim for asthma. For each utilization case, we randomly selected five person-days with no asthma claim as non-utilization controls. We defined an asthma claim as a medical claim with at least one International Classification of Disease Version 9 (ICD-9) diagnosis code of 493x or International Classification of Disease Version 10 (ICD-10) of J45x. We repeated the analysis using only asthma emergency department (ED) claims.

We used a logistic regression model within the DLNM, with person-day case vs control as the response variable. The primary exposure variable was smoke $PM_{2.5,}$ determined by date and residential zip code, with time lags from 0 to 14 days. We controlled for members' sex, age category, (0-17, 18-64, 65+) and primary insurance (Medicaid, Medicare, Commercial). We used zip-code tabulation area (ZCTA) level poverty from the American Community Survey [20] to control for association between smoke exposure and neighborhood socioeconomic status. Individual level socioeconomic information is not available in WA-APCD. We controlled for year to account for year-to-year changes in the study population, and we controlled for day of the week to eliminate temporal autocorrelation due to weekly office schedules. We controlled for temperature and humidity using wet-bulb temperature at lag 0.

The study design produced clustering in the data that could not be accounted for in the DLNM model. Person-days are clustered within persons, and persons are clustered within zip-codes. Cases and controls are determined at the person-day level. Age, sex and primary payer are individual level, while smoke exposure, wet-bulb temperature and neighborhood poverty are all assigned at the zip code level. To assess the impact of this omission, we ran a subsequent analysis using a multilevel mixed effect regression model with person nested in zip-code as random effects.

We performed analyses in RStudio, version 1.4.1717 [21]. We used package "dlnm" [22] for the DLNM models, and package "glmmTMB" [23] for multilevel mixed effect models.

Results

Study population

Of 6,744,791 WA-APCD members insured from 2014-2018, 6,027,481 were continuously enrolled for one or more fire seasons. Of these, the study population included 332,120 members with at least one asthma claim, and 83,777 members with at least one asthma ED claim. There were 770,545 person-days with asthma related medical claims, and 129,749 person-days with asthma related ED claims. The study population had a higher percentage of female members and a higher percentage of Medicaid recipients compared with the general WA-APCD population (Table 2).

Table 2. Demographic characteristics of the study population compared to the WA-APCD general population.

	Number in Study Population	Percent in Study Population	Percent in WA-APCD
Female	205,965	62.0	54.9
Male	126,390	38.0	45.1
Age < 18	88,242	26.1	26.2
Age 18-64	173,576	51.4	50.7
Age 65+	76,136	22.5	23.0
Commercial	97,785	27.1	35.6
Medicaid	171,213	47.5	40.7
Medicare	91,483	25.4	23.7

Asthma-related claims

Members with asthma had increased odds of having a medical claim for asthma on days with wildfire smoke exposure, and for up to 10 days following exposure (Figure 1). There was an immediate effect on the day of exposure and for two days following, and there was a delayed effect from 5-10 days following exposure. The effect was greatest on the day following exposure. A 10 µg/m^3 wildfire $PM_{2.5}$ smoke exposure for one day was associated with a 3%cumulative increase in the odds of having an asthma related medical claim over the next 10 days (OR 1.03, 95% CI 1.03 – 1.04).

Smoke exposure was associated with an immediate increase in emergency department claims on the day of exposure, with no significant delayed effect (Figure 2). A 10 µg/m^3 wildfire $PM_{2.5}$ smoke exposure for one day was associated with a 2% increase in the odds of having an asthma-related ED claim on the day of exposure (OR 1.02, 95% CI 1.01 – 1.03).

Figure 1. Association of asthma medical claims and wildfire smoke. Odds ratios per 10 µg/m^3 $PM_{2.5}$ up to 14 days following exposure.

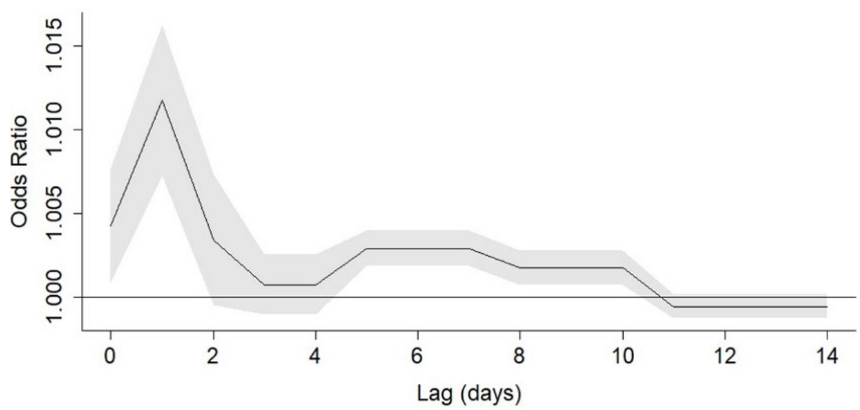
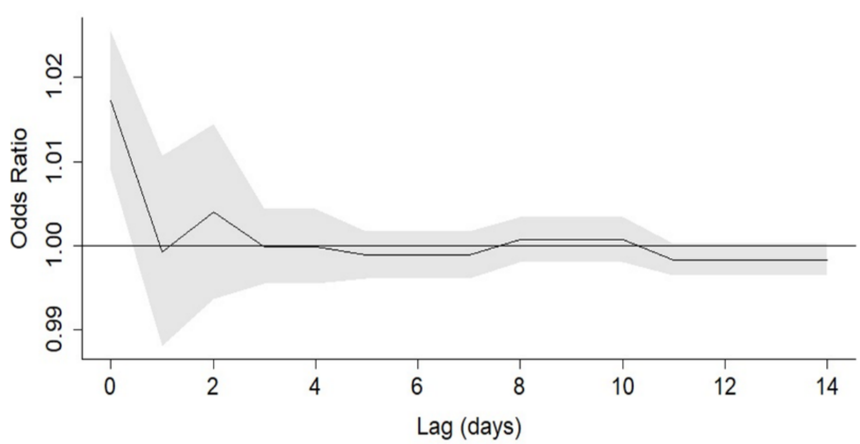


Figure 2. Association of asthma ED claims and wildfire smoke. Odds ratios per 10 µg/m3 PM2.5 up to 14 days following exposure.



We converted the odds ratios from the DLNM model into risk ratios, and applied them to the distribution of exposure histories in the study population (Table 1). Smoke exposure accounted for 7,262 excess asthma claims including 609 excess asthma ED visits in the study population over 5 years. Based on the average cost of $624 for an asthma claim, this represents $4.5 million in excess medical cost.

To test the impact of clustering on the data, we ran a series of multi-level mixed effects models (MLM) using exposure lags determined by the results of the DLNM model. For asthma claims, we ran two models, using smoke $PM_{2.5}$ at lag 1, and the moving average of lags 0-2 as exposure variables. For asthma ED claims, we used smoke $PM_{2.5}$ at lag 0. We ran each model with and without random effects, for a total of 6 models (Table 3). Odds ratios from the MLM models were close to those from the DLNM. The random effects, though statistically significant, did not greatly change the odds ratios for smoke exposure, suggesting that clustering in the data did not introduce undue bias to the DLNM results above.

Table 3. Multi-level mixed effect models with and without random effects

Exposure Lag	Odds ratio: with clustering	Odds ratio: no clustering
Asthma medical claims		
Lag 1	1.02	1.02
3-day average	1.03	1.02
Asthma ED claims		
Lag 0	1.02	1.02

Other conditions

We applied the same methods to medical and ED claims for chronic obstructive pulmonary disease, ischemic heart disease, cerebrovascular disease, and hypertension. We found no significant associations of smoke exposure to any of these conditions except one. $PM_{2.5}$ exposure was associated with a less than 1% decrease in hypertension medical claims (OR 0.994, 95%CI 0.992-0.996) at lag 0. Though statistically significant, we suspect this is a spurious result due to extremely large sample size (3.4 million case person-days) and is of no clinical importance.

Discussion

This study examined the immediate, short-term impact of a wildfire smoke event on healthcare utilization for asthma. We found a small but discernable increase in utilization both in medical and emergency department asthma claims, costing $4.5 million over 5 years. This is likely an underestimate for several reasons. First is the difficulty of assessing individual exposure to air pollution. Members who live in an exposed zip code would be classified as exposed, even if they stay indoors and have no actual personal exposure. Similarly, a person who lives in an unexposed zip code but commutes to an exposed zip code would be classified as unexposed. This misclassification error would almost certainly dilute any effect we might see. Second, our methodology only considers the immediate, short-term impact – up to 14 days lag – of a discrete wildfire smoke event. But air pollution is also known to exacerbate many chronic illnesses. If multiple smoke exposures over the course of a season worsens an asthma patient's baseline condition, it could increase utilization throughout the year. The effect might be substantial but would not be detected by this method.

This could also explain why we failed to find any significant increase in COPD, ischemic heart disease, cerebrovascular disease, or hypertension. While the long-term effect of air pollution on these chronic conditions is well established, it may not manifest as increased utilization immediately following a smoke event. Asthma is a chronic condition like the others but is also the most susceptible to acute exacerbations in response to environmental triggers, including smoke.

This study identified a short-term effect of wildfire smoke on healthcare cost and utilization for one health condition. Wildfire smoke also exacerbates long-term chronic health conditions, further increasing morbidity, utilization, and cost. Add to this non-medical costs such as lost work days and reduced disability-free life expectancy, and the full impact of wildfire smoke on health and well-being in Washington may be considerable.

Caveats

We have already discussed limitations in assessing wildfire smoke exposure, and our inability to detect long-term chronic effects. We should also acknowledge a few further limitations in the data and methods.

The WA-APCD does not perfectly represent the population of Washington state. In particular, though the data includes Medicare Advantage for all years, Medicare Fee-For-Service claims are only included for 2015-2017. The commercially insured population is also under-represented. Uninsured residents are not represented at all.

Results from the DLNM method can be influenced by the choice of functional form for the exposure. We chose a stratified function to avoid imposing any particular shape to the results, and to better capture discontinuities in response, but this came at the expense of wide confidence intervals and loss of power. We chose a linear function to model the response to $PM_{2.5}$ concentration. There were indications of a non-linear relationship, with greater effect at higher concentration, but it was not clear enough to reject the linear model.

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