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Ambient particulate matter, landscape fire smoke, and emergency ambulance dispatches in Sydney, Australia

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ABSTRACT

Background: Emergency ambulance dispatches (EAD) are a novel outcome for evaluating the public health impacts of air pollution. We assessed the relationships between ambient particulate matter (PM) from all sources, PM from landscape fire smoke (LFS), and EADs likely to be associated with cardiorespiratory problems in the Sydney greater metropolitan region for an 11-year period from 2004 to 2015.
Methods: EAD codes are assigned at the time of the call to emergency services using standard computer assisted algorithms. We assessed EADs coded as: breathing problems, chest pain, stroke or cerebrovascular accident (stroke), cardiac or respiratory arrest and death (arrest), and heart or defibrillator problems (other heart problems). Using a daily times series study design with a generalized linear Poisson regression model we quantified the association between EAD and daily $PM_{2.5}$ from all sources ($PM_{2.5,all}$) and $PM_{2.5}$ primarily due to LFS ($PM_{2.5,LFS}$).
Results: Increases of 10 $\mu g \cdot m^{-3}$ in $PM_{2.5,all}$ were positively associated with same day EAD for breathing problems (RR = 1.03, 95% CI 1.02 to 1.04), arrest (RR = 1.03, 95% CI 1.00 to 1.06), and chest pain (RR = 1.01 CI 1.00 to 1.02) but not with other outcomes. Increases of 10 $\mu g \cdot m^{-3}$ $PM_{2.5,LFS}$ were also positively associated with breathing problems on the same day (RR = 1.04, 95% CI 1.02 to 1.05) and other heart problems at lag of two days (RR = 1.05, 95% CI 1.01 to 1.09).
Conclusions: Emergency dispatches for breathing problems are associated with $PM_{2.5,all}$ and $PM_{2.5,LFS}$ and provide a sensitive end point for continued research and surveillance activities investigating the impacts of daily fluctuations in ambient $PM_{2.5}$.

1. Introduction

The association between ambient particulate matter (PM) and adverse health outcomes has been clearly established, yet evidence gaps remain. For example, the relative impacts of particles from different sources are still under active investigation, and some health outcomes have not been well characterised because relevant datasets are not readily available to researchers (Englert, 2004; Davidson et al., 2005; Pope and Dockery, 2006).

Sources of PM include traffic, industrial emissions, re-suspension of dust, sea salt, atmospheric formation of secondary particles, and biomass burning. The contribution of each source to the total PM concentration varies both spatially and temporally (Belis et al., 2013). Landscape fire smoke (LFS) is a major source of $PM_{2.5}$ (PM less than 2.5 μm in aerodynamic diameter) in many areas, with a global estimate of 340,000 premature deaths attributable to LFS each year (Johnston et al., 2012). However, studying the population health impacts of LFS is challenging for many reasons: (1) episodes of LFS are typically unpredictable and short-lived; (2) the spatial and temporal distributions of smoke impacts are much different from those of PM from other, well-monitored sources; (3) the exposure affects densely populated urban areas and sparsely populated rural areas; and (4) severe smoke events can cause much higher peak concentration than PM from other sources.

Many studies of LFS exposure have examined its association with emergency room visits, hospital admissions, or mortality. However, these data are not ideal for capturing the spatial and temporal variations in health status that might be associated with LFS, because the exposure location is not accurately geolocated and/or time-stamped. Furthermore, these data are typically not available in near-real-time, which limits their utility for public health surveillance of air quality events. Emergency ambulance dispatches (EAD) are systematically collected, centrally logged, geolocated, and time-stamped, making them potentially useful for both retrospective research and prospective surveillance

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related to LFS exposures. However, the utility of these data has been relatively unexplored with respect to air pollution, while they have been used in research and surveillance related to injuries and outbreak of infectious disease (Mostashari et al., 2003; Schuurman et al., 2008).

A limited number of studies published to date suggest that data collected by ambulance services, including EAD codes, paramedic assessment codes, and specific clinical data could be endpoints sensitive to ambient air quality. For example, Michikawa et al. (2014) and Zauli Sajani et al. (2014) observed a positive association between increased PM and EAD for non-traumatic causes, especially for respiratory causes. Youngquist et al. (2016) found associations between ambient $PM_{2.5}$ and diabetic symptoms and fainting. More specifically, Dennekamp et al. (2015), Haikerwal et al. (2015) examined data from the cardiac arrest registry of the Victorian Ambulance Service and identified clear positive associations between LFS, $PM_{2.5}$ and out-of-hospital cardiac arrests. In this study we aimed to (1) evaluate the sensitivity of different EAD codes to ambient $PM_{2.5}$ from all sources ($PM_{2.5,all}$) and ambient $PM_{2.5}$ predominantly derived from LFS ($PM_{2.5,LFS}$) and (2) quantify the association between $PM_{2.5,all}$ and $PM_{2.5,LFS}$ with dispatch codes most likely to be associated with cardiovascular or respiratory problems.

2. Methods

2.1. Study population and outcome data

Sydney, the capital of the state of New South Wales (NSW), is the largest city in Australia with a population of approximately 4.9 million in the greater Sydney metropolitan region. We received EAD data from the Ambulance Service of NSW for 1 January 2004 through 31 December 2014. Information extracted from the EAD included the date and time of the call, geographical coordinates of the event, and the reason for the call. Calls were recorded following the Medical Priority Dispatch System (MPDS), which is a standardized computer assisted response algorithm produced by the International Academies of Emergency Dispatch (IAED). It is used by more than 20 different countries, including Australia, the United Kingdom, and the United States (Clawson et al., 2008; IAED, 2016). In response to standard questions and protocols, the MPDS classifies the severity of the incident and assigns one of 28 codes to identify the broad category of health problem. Of these, we assessed all dispatches for codes that could plausibly include cardiovascular or respiratory medical conditions, which are known to be sensitive to short-term changes in air quality (Atkinson et al., 2014).

Ambulance dispatches within the greater Sydney metropolitan region were extracted from the NSW dataset. Only those records with the following MPDS code numbers were included in our analyses: 6 = breathing problems; 9 = chest pain; 10 = cardiac or respiratory arrest and death (arrest); 28 = stroke or cerebrovascular accident (stroke); and 19 = heart or defibrillator problems (other heart problems). Although the descriptors are systematically allocated, it is important to remember that they do not represent specific medical conditions and can include many problems unrelated to cardiovascular and respiratory diseases. To characterise the nature of the range of problems included in each EAD we evaluated paramedic assessments that were available for a subset of the data for the period 5 January 2010 through 31 December 2014. Paramedic assessments can include symptoms (e.g. pain), signs (e.g. hypertension), clinical diagnosis (e.g. asthma) or be reported as unknown, or no problem identified.

Dispatches from 1 January 2004 through 17 May 2004 and from 1 January 2010 through 1 July 2011 were excluded due to poor data completeness associated with changes in data collection systems. Only non-traumatic emergency dispatches were included in our analyses. Elective dispatches (e.g. transferring patients from one hospital to another) were excluded.

2.2. Ambient air pollution and meteorology data

The NSW Department of Planning and Environment measures hourly $PM_{2.5}$ concentrations using beta attenuation monitors at four sites across the greater Sydney metropolitan region. Temperature and relative humidity (RH) are also measured at 16 sites. All $PM_{2.5}$ and temperature data from these sites were obtained for the same period as the EAD data. Daily city-wide average $PM_{2.5}$ concentrations were calculated following the methods of Katsouyanni et al. (2009). In brief, daily averages for each site were calculated when at least 75% of the hourly values were available, and were otherwise set to missing. The missing value for a specific pollutant from a specific site was replaced by the mean level of the other sites multiplied by a factor equal to the ratio of the seasonal mean of the missing site divided by the corresponding mean from the other sites. Sites with more than 25% of missing values for the whole period of the analysis were excluded.

2.3. Landscape fire smoke

In previous work we developed a database of validated LFS days from 1997 through 2007 (Johnston et al., 2011b), and we added 2008 through 2013 for this study following the same methods. In brief, days on which the daily $PM_{2.5}$ or PM_{10} exceeded the 95th percentiles ($13.8\ \mu g \cdot m^{-3}$ and $30.8\ \mu g \cdot m^{-3}$, respectively) over the entire time series were flagged as potentially affected by LFS. Potential LFS days were further examined using satellite imagery and electronic news archives to confirm the days where elevations in PM could be attributed to smoke from landscape fires. All days in the time series were assigned a binary LFS variable, which took a value of 1 for validated smoke days and 0 otherwise.

2.4. Statistical analysis

Generalized linear quasi-Poisson regression models were used to estimate the effect of daily $PM_{2.5,all}$ concentrations on the number of ambulance dispatches for the chosen codes (Eq. (1)):

$$\begin{aligned} &Y_t \sim \text{Poisson}(\mu_t) \\ &\text{Log}(\mu_t) = \beta_0 + \beta_1 PM_{2.5,allt} + \beta_2 O_{3maxt} + s(T_t, 2) \\ &\quad + s(T_{lag(t,1-3)}, 2) + S(RH_t, 2) + s(RH_{lag(t,1\text{-}3)}, 2) \\ &\quad + s(t, df \times \#\text{years of data}) + \beta_4 DOW_t \\ &\quad + \beta_5\ \text{public holiday} + \beta_6 \text{influenza} = \beta_0 + \beta_1 PM_{2.5t} + COVs \end{aligned} \tag{1}$$

where: t is the day of the observation; Y is the observed number of dispatches; $PM_{2.5,all}$ is the daily city wide average $PM_{2.5}$ concentration; O_{3max} is the 1 h daily maximum of ozone concentration; s(T,2) is a natural cubic spline of the average temperature with two degrees of freedom (df), and the *lag* (1–3) is the running average for the previous three days; RH is the average relative humidity; DOW is the categorical day of the week; Public holiday is a binary variable indicating whether day *t* was a public holiday; Influenza is a binary variable indicating whether day *t* was an epidemics of influenza. A spline on the day of observations with eight df per year was used to control for long term trends. The number of df and lag structures for RH and T, except for same day RH which we used spline with two df instead of a linear function, were based on previous work in a similar population (Johnston et al., 2011a).

Individual models were run separately for same day (lag 0), lag 1, and lag 2 of $PM_{2.5,all}$ concentrations to assess the temporal relationship. To compare the effect of $PM_{2.5,lfs}$ with $PM_{2.5,all}$, another set of models was used (Eq. (2)).

$$\begin{aligned} &Y_t \sim \text{Poisson}(\mu_t) \\ &\text{Log}(\mu_t) = \beta_0 + \beta_1 PM_{2.5,nonLFSt} + \beta_2 PM_{2.5,LFSt} + COVs \end{aligned} \tag{2}$$