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# Air pollution, weather, and respiratory emergency room visits in two northern New England cities: an ecological time-series study

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## Abstract

Daily emergency room (ER) visits for all respiratory (ICD-9 460-519) and asthma (ICD-9 493) were compared with daily sulfur dioxide ($SO_2$), ozone ($O_3$), and weather variables over the period 1998–2000 in Portland, Maine (population 248,000), and 1996–2000 in Manchester, New Hampshire (population 176,000). Seasonal variability was removed from all variables using nonparametric smoothed function (LOESS) of day of study. Generalized additive models were used to estimate the effect of elevated levels of pollutants on ER visits. Relative risks of pollutants are reported over their interquartile range (IQR, the 75th –25th percentile pollutant values). In Portland, an IQR increase in $SO_2$ was associated with a 5% (95% CI 2–7%) increase in all respiratory ER visits and a 6% (95% CI 1–12%) increase in asthma visits. An IQR increase in $O_3$ was associated with a 5% (95% CI 1–10%) increase in Portland asthmatic ER visits. No significant associations were found in Manchester, New Hampshire, possibly due to statistical limitations of analyzing a smaller population. The absence of statistical evidence for a relationship should not be used as evidence of no relationship. This analysis reveals that, on a daily basis, elevated $SO_2$ and $O_3$ have a significant impact on public health in Portland, Maine.

*Keywords:* Air pollution; Emergency room; Time-series; Asthma; Respiratory

## 1. Introduction

Air quality monitoring is conducted primarily with observation of concentrations and mixing ratios of potentially dangerous compounds in the troposphere in comparison with some standard, such as the National Ambient Air Quality Standards (NAAQS) established by the US Environmental Protection Agency. In addition to simply monitoring air quality as it changes over time, it is also important to monitor how that changing air quality is affecting human health. From a public health perspective, impacts such as elevated emergency room (ER) visits are an important supplement to other air quality metrics and useful in gauging the effectiveness of air pollution controls (Weisel et al., 2002). Based on the findings of other studies, it is clear that short-term exposure to air pollution negatively affects human health (e.g., Brunekreef and Holgate, 2002). While a multitude of city-wide ecological studies have been completed on this topic around the world, none have investigated ER visits in New England, home to over 14 million people and a region that experiences unique air quality and weather phenomenon. Many New England counties are nonattainment areas for ozone pollution as defined by NAAQS and thus it is likely that pollution is associated with negative health impacts (EPA Region 1, 2002). Sulfur dioxide is another commonly present air pollutant, although it is rarely in exceedence of the NAAQS. Until this study, the

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importance of this pollution as a factor affecting ER visits has simply been inferred for the region from studies in other areas. The need for a better understanding of this relationship was established at the Conference of the New England Governors and the Eastern Canadian Premiers, where air quality and health research was identified as a priority in the region (NEG/ECP, 2002). For New England, the only question remaining regards the nature and significance of the effects.

In this study the effects of $SO_2$ and $O_3$ on respiratory and asthma ER visits are investigated in the Hospital Service Areas (HSA) of the two largest cities in northern New England: Portland, Maine (HSA population 248,000), and Manchester, New Hampshire (HSA population 176,000). The HSA is essentially the area served by the cities' hospitals.

## 2. Materials and methods

ER data are collected by individual hospitals and reported to state hospital associations in both Maine and New Hampshire. The Portland, Maine, ER data were provided by the Public Health Research Group, in Portland, via the Maine Lung Association. The Manchester, New Hampshire, ER data were provided by the Manchester Health Department and the New Hampshire Department of Health and Human Services. The ER databases were queried to create a time-series of daily counts of individuals for all respiratory complaints (ICD-9 codes 460–519) and asthma (ICD-9 codes 493), for all ages, 0–14, 15–64, and 65+ for the time period January 1, 1998 (1996 for Manchester), through December 31, 2000. In addition, influenza (ICD-9 487) was included in models to account for flu epidemics. Total daily visits for gastroenteritis (ICD-9 558), which is unlikely to be related to air quality or weather, were used as a control diagnosis. The counts were limited to individuals residing and visiting an ER facility within the HSA of the respective city.

Air chemistry data were compiled from the EPA Aerometric Information Retrieval System (AIRS) database, as recorded by single monitors in both cities. Sulfur dioxide ($SO_2$) data were collected hourly and condensed into daily average and daily 1-h maximum; ozone ($O_3$) data were collected by the EPA only for the period from April to October (with the exception of the winter of 1997–1998 in Portland) and were condensed into the daily 1 h max, daily maximum 8 h average, and daily 24-h average. Fine particulate matter ($PM_{2.5}$) was only available with daily resolution for the year 2000, which was too short of a time frame for this analysis and therefore was not used.

It has been known for decades that weather plays a role in aggravating respiratory ailments (Ribon et al., 1972; Jamason et al., 1997). Thus it is important to account for the effect of changes in the weather when modeling ER visits. Meteorological data (maximum temperature, minimum temperature, and relative humidity) on the same day and the prior 2 days were included in the analysis. Meteorological data are from the National Oceanic and Atmospheric Administration's National Climatic Data Center. Stepwise procedures selected one form of temperature variable and one form of relative humidity for each diagnosis.

## 3. Study design

This study was completed using multiple regression analysis to model the health outcome variables as functions of air pollution, weather, and time. The ultimate goal was to isolate the effect of individual pollutants and weather phenomenon to understand the association of increases in certain pollutants with increases in ER visits.

Four models were constructed consisting of "All Respiratory" and "Asthma" visits in Portland and Manchester, for all ages. Terms were considered for inclusion in a stepwise process that evaluated several forms of each predictor and considered both parametric and nonparametric relationships. A nonparametric smoothed function (LOESS) of time is used to remove low-frequency variability (Cleveland, 1988). This procedure removes smooth long-term variability in the time-series and has been successfully used to remove seasonal variability from similar datasets in many previous studies (Stieb et al., 2000; Lin et al., 2002; Wong et al., 2002). Smoothing windows were selected for both diagnoses in both cities from several possible fractions of the annual cycle (365, 182.5, 121, 91, 61, 46, 30 days), as conducted by Stieb et al. (2000). The filtering parameter used to remove seasonal variability was selected by minimizing autocorrelation of residuals, reviewing residual plots, and minimizing the Akaike Information Criterion (AIC) (Cakmak et al., 1998). The AIC is essentially a measure of goodness of fit that penalizes for model complexity (Sakamoto et al., 1986). The smoothing parameter identified for each diagnosis was also used to smooth the atmospheric variables in the models to ensure comparison of identically smoothed data and reduce the possibility of introducing spurious associations.

Seasonality was removed from predictor variables prior to including them in the model. The seasonality of the ER data was smoothed within the model to retain Poisson distribution of the data. This method, termed preadjustment, removes seasonal confounding among variables (Burnett et al., 2001). Estimates using preadjusted data reflect the true relationship between short-term fluctuations in atmospheric variables and ER visits.

Modeling health effects without removing the seasonality of predictors has the advantage of revealing the sum of short-term and mid-term effects but has more potential for confounding by unrelated risk factors. Thus relative risk estimates derived from preadjusted data, as done here, should be considered conservative.

It was assumed that the residual variance was proportional to the expected number of ER visits, thus accounting for over and underdispersion of the Poisson distribution. Log-relative risks were estimated using generalized additive models (Hastie and Tibshirani, 1999) built with S-Plus Software (Insightful, 2000). Due to the unsuitability of 8 default convergence parameters for this type of research, more stringent parameters ($\varepsilon = 10^{-15}$, $M = 1000$, $\varepsilon_{\mathrm{bf}} = 10^{-15}$, $M_{\mathrm{bf}} = 1000$) were used in the modeling (Dominici et al., 2002). After determining the most appropriate temporal filtering parameter, stepwise procedures selected the most appropriate form of temperature and humidity. The process also evaluated whether the relationship was best characterized by a linear or smoothed (LOESS with 50% span) term. All models included a term for day-of-the-week and regression intercept. After determining the best model for each of the four classes, it was run for the different age groups to determine the relative risk of elevated pollutant levels using the following model:

$$E(y_t) = \mathrm{e}^{(\alpha + S_{X1} + S_{X2} + \cdots + S_{Xn})},$$

where $E(y_t)$ is the expected number of ER visits per day, e is the exponential function (2.718), $\alpha$ is the model intercept, and $S_{X1}$–$S_{Xn}$ are the filtered, smoothed (or linear) functions of predictor variables.

## 4. Results

ER visits experienced pronounced seasonal variation in both cities, with 20–30% fewer admissions in the summer than in the winter in both cities (Figs. 1 and 2). A 30-day smoothing parameter was chosen for all diagnostic classes to remove temporal cycles, minimize autocorrelation, and optimize goodness of fit. Table 1 summarizes all terms by season. After selecting the 30-day filtering parameter, it was applied to all predictor variables to filter seasonality from them as well. For example, Figs. 3 and 4 make the benefit of preadjustment apparent for the Manchester data. If the raw data in Fig. 3 were used in the model, admissions would be negatively associated with temperature and positively associated with $SO_2$. However, much of that relationship would be due primarily to their seasonality, rather than day-to-day variation. Fig. 4 displays the data after removing variability greater than 30 days, and eliminates the possibility of spurious associations due to seasonality.

In addition to reducing the possibility of residual confounding between the predictors and the response, a significant benefit of preadjustment is the removal of potentially spurious associations between predictor variables (Table 2). For example, $SO_2$ tends to be highest in winter months, when temperature is lowest. Simply regressing these variables reveals a negative association ($R^2 = -0.22$ for $SO_2$ and maximum temperature in Manchester, for example). However, removal of long-term trends removes this relationship ($R^2 = 0.02$). Including the raw data in a model would result in collinearity that would need to be accounted for, but removing it first reduces that problem for several variables.

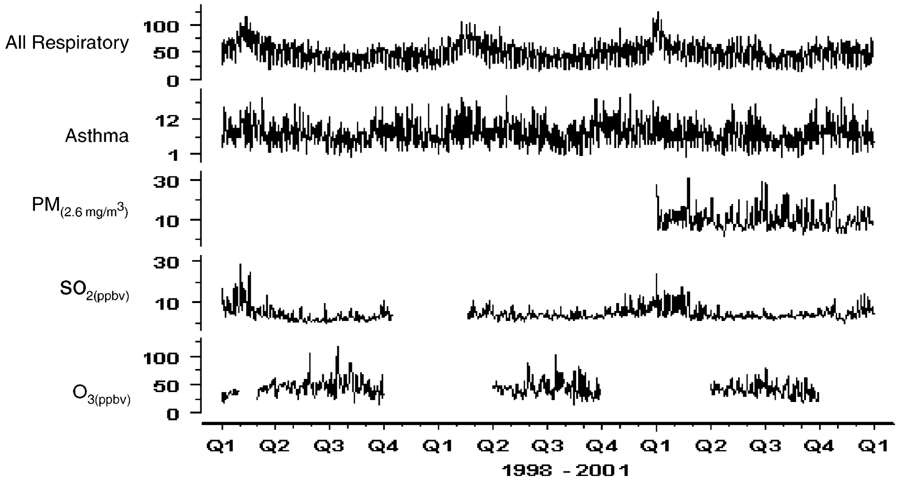

Fig. 1. Counts of ER visits and air quality in Portland, ME, 1998–2000. All respiratory is a daily count of visits for all respiratory reasons. Asthma is a daily count of visits for asthma. $SO_2$ is the 24-h average value of sulfur dioxide. $O_3$ is the daily maximum 8-h average value. The labels on the $x$ axis refer to quarters of the year, i.e., Q1, January; Q2, April; Q3, July; Q4, October.

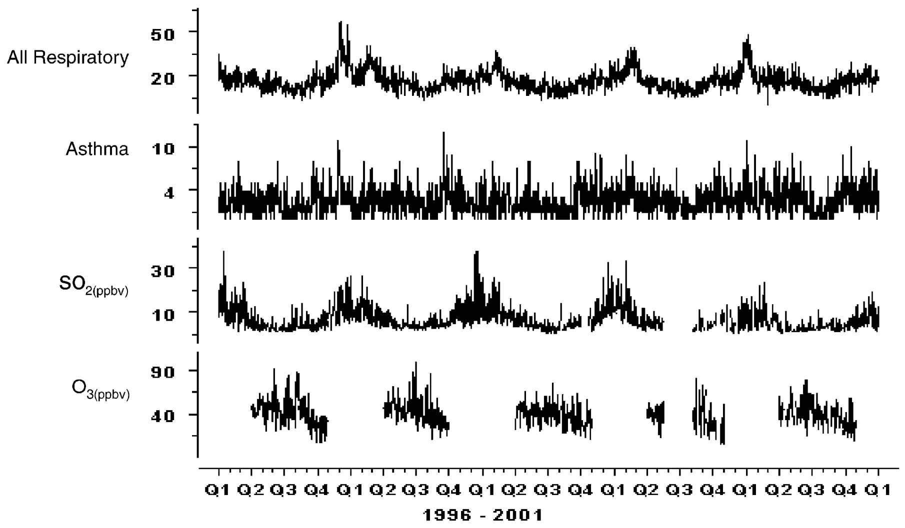

Fig. 2. Counts of ER visits and air quality in Manchester, NH 1996–2000. All respiratory is a daily count of visits for all respiratory reasons. Asthma is a daily count of visits for asthma. $SO_2$ is the 24-h average value of sulfur dioxide. $O_3$ is the daily maximum 8-h average value. The labels on the *x* axis refer to quarters of the year, i.e., Q1, January; Q2, April; Q3, July; Q4, October.

Table 1
Mean (standard deviation) of atmospheric variables and emergency room visits for Portland, ME, and Manchester, NH

| Variable | Full year (Mar–May) | Winter (Dec–Feb) | Spring (Mar–May) | Summer (Jun–Aug) | Fall (Sept–Nov) |
|---|---|---|---|---|---|
| *Portland, ME* | | | | | |
| $SO_2$ (1 h max ppbv) | 11.1 (9.1) | 17.1 (12.0) | 10.0 (7.1) | 9.1 (8.0) | 9.7 (7.1) |
| $O_3$ (max 8 h mean ppbv) [a] | 43.1 (13.5) | 33.2 (5.7) | 43.7 (10.2) | 46.1 (15.4) | 35.9 (12.0) |
| Max daily temp (°C) | 13.8 (10.0) | 2.1 (5.4) | 12.6 (6.6) | 24.9 (4.1) | 15.2 (6.6) |
| Min daily temp (°C) | 3.5 (9.3) | −7.4 (6.2) | 2.2 (5.4) | 14.0 (3.3) | 4.8 (6.1) |
| Relative humidity (%) | 70.8 (12.6) | 68.0 (13.8) | 68.7 (13.9) | 73.9 (9.6) | 72.6 (11.8) |
| Asthma | 7.4 (3.8) | 7.8 (4.0) | 7.4 (3.6) | 6.0 (3.4) | 8.3 (4.0) |
| All respiratory | 49.0 (19.2) | 59.0 (21.9) | 51.1 (18.3) | 39.6 (14.2) | 46.5 (16.5) |
| *Manchester, NH* | | | | | |
| $SO_2$ (1 h max ppbv) | 16.5 (14.7) | 25.7 (15.8) | 14.8 (12.0) | 10.6 (15.1) | 14.6 (11.1) |
| $O_3$ (max 8 h mean ppbv) | NA | NA | 43.4 (9.7) | 42.8 (14.6) | 30.6 (11.5) |
| Max daily temp (°C) | 14.6 (10.9) | 1.8 (5.7) | 13.5 (8.0) | 26.6 (4.1) | 15.7 (7.6) |
| Min daily temp (°C) | 2.1 (9.9) | −8.8 (6.6) | 0.4 (6.4) | 13.1 (3.8) | 7.0 (3.1) |
| Relative humidity (%) | 68.5 (11.6) | 68.5 (12.8) | 63.9 (13.1) | 70.5 (8.8) | 70.8 (10.1) |
| Asthma | 2.6 (1.9) | 2.9 (1.9) | 2.6 (1.7) | 1.8 (1.4) | 3.2 (2.1) |
| All respiratory | 16.6 (7.0) | 22.5 (8.1) | 16.2 (5.4) | 11.1 (3.6) | 16.8 (5.1) |

[a] Portland winter $O_3$ levels only recorded during fall/winter of 1997–1998. Spring $O_3$ measurements are generally only for April–May. Fall $O_3$ measurements generally only for September–October.

The predictor forms selected by the stepwise procedure are listed in Table 3. The selected variables were fairly consistent between cities, with flu epidemics being important for all respiratory admissions but not asthma in both cities. Precipitation was only significant in Portland for all respiratory visits. However, sensitivity analysis revealed that differences between the selected terms was small and made little difference to the relative risks estimated by the model. Terms selected using unfiltered predictor data were similar to those in Table 3. The models described in Table 3, with the addition of a term for the 24-h average $SO_2$ value, explain from 31% to 78% of the variability in ER visits (Fig. 5). To investigate whether there are unequal effects on certain age groups, the models were also run for four age classes: all ages, 0–14, 15–64, and 65+. The mean daily visits for each age group are summarized in Table 4.

Before estimating the relative risk posed by elevated pollutant levels, the form of the pollutant–response relationship was investigated by including the pollutant in the model as a nonlinear term (LOESS smooth with an 80% span). In most cases the form was near linear (Fig. 6). Thus, relative risk estimates from linear

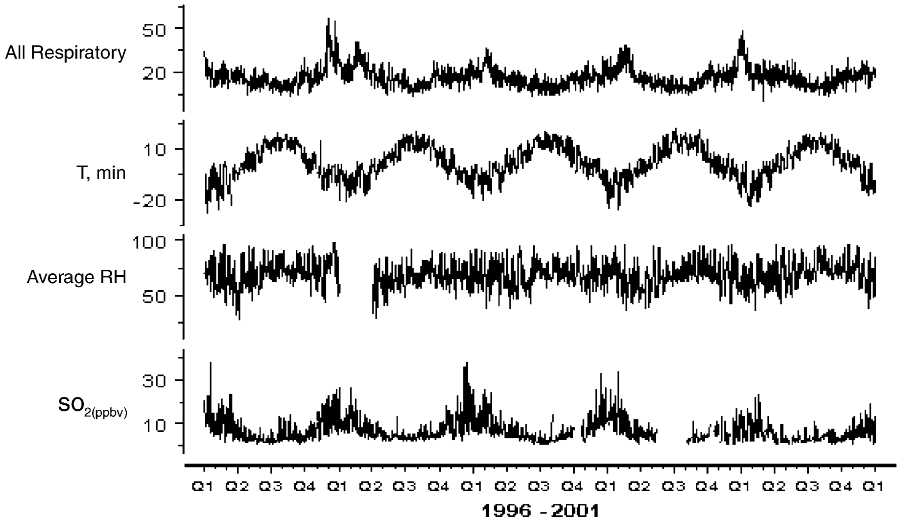

Fig. 3. Manchester all respiratory ER visits, minimum temperature (°C), average relative humidity (%), and $SO_2$ from 1996 to 2000. The labels on the $x$ axis refer to quarters of the year, i.e., Q1, January; Q2, April; Q3, July; Q4, October.

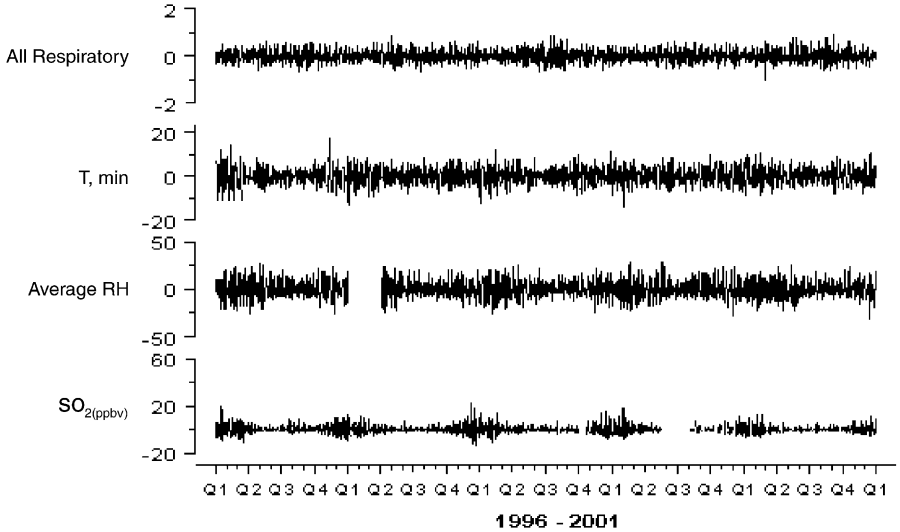

Fig. 4. Anomalies of Manchester all respiratory ER visits, minimum temperature (°C), average relative humidity (%), and $SO_2$ from 1996 to 2000. Data have been filtered using a LOESS smother to remove variability greater than 30 days. The labels on the $x$ axis refer to quarters of the year, i.e., Q1, January; Q2, April; Q3, July; Q4, October.

approximations remain a useful tool for understanding dose–response relationships in these two cities. Stepwise procedures selected the 5-day average $SO_2$ value (average mixing ratio from the same day and the prior four) for all diagnostic categories except asthma in Portland, where the 1-day average was found to be the most significant. Similarly, the 5-day 24-h average $O_3$ was selected as the most significant for all classes except Manchester asthma visits (for which the max 8-h average was selected). However, to make comparisons consistent among classes and with other published studies, the daily 24-h average $SO_2$ and max 8-h $O_3$ were selected for further analysis.

Relative risks due to both an interquartile change (the difference between the 25th and the 75th percentile) and a 10 $\mu g/m^3$ change in pollutant (as commonly reported in other studies) were estimated (Table 5). The same analysis was completed for gastroenteritis, the control diagnosis. There were no significant associations between gastroenteritis and pollution in either city.

In Portland, elevated levels of $SO_2$ are associated with significant increases in ER visits for most age groups in both diagnoses (Fig. 7). Relative risks for an interquartile range (IQR) change of 6.3 ppbv ranged from 5% in all respiratory visits to 10% increases in asthmatic elders. In Portland, an IQR increase in $SO_2$ levels was

Table 2
Correlation coefficients among meteorological and pollutant variables

| | Raw data | | | | Filtered data | | | |
|---|---|---|---|---|---|---|---|---|
| | $SO_2$ | $T_{max}$ | $T_{min}$ | AveRH | $SO_2$ | $T_{max}$ | $T_{min}$ | AveRH |
| *Portland* | | | | | | | | |
| $O_3$ [a] | 0.05 | 0.36 | 0.24 | −0.11 | 0.24 | 0.15 | 0.24 | −0.04 |
| $SO_2$ | | −0.30 | −0.39 | −0.13 | | 0.15 | −0.15 | −0.11 |
| $T_{max}$ | | | 0.87 | −0.03 | | | 0.42 | −0.23 |
| $T_{min}$ | | | | 0.30 | | | | 0.42 |
| *Manchester* | | | | | | | | |
| $O_3$ [a] | 0.01 | 0.42 | 0.15 | −0.36 | 0.05 | 0.50 | 0.12 | −0.28 |
| $SO_2$ | | −0.47 | −0.55 | 0.06 | | 0.16 | −0.15 | 0.14 |
| $T_{max}$ | | | 0.87 | 0.05 | | | 0.35 | −0.10 |
| $T_{min}$ | | | | 0.31 | | | | 0.43 |

Pearson *R* correlation coefficients for meteorological and air pollution data for two cities. Filtered data have seasonal variability (>30 days) removed. $O_3$ is the maximum 8-h average of each day. $SO_2$ is the 24-h average mixing ratio of sulfur dioxide. $T_{max}$ is the daily maximum recorded temperature. $T_{min}$ is the daily minimum recorded temperature. AveRH is the average of the minimum and maximum daily recorded relative humidity.

[a] Coefficients including $O_3$ are only for April–October. All other correlations are for year-round data.

Table 3
Final predictor forms selected by the stepwise procedure for each city/diagnosis model

| City | Outcome | Influenza | Temperature | Average humidity | Precipitation |
|---|---|---|---|---|---|
| Portland | All respiratory | Yes | Min, S, Lag 0 | Lag 0 | Yes |
| | Asthma | No | Max Lag 2 | Lag 0 | No |
| Manchester | All respiratory | Yes | Min Lag 2 | Lag 1 | No |
| | Asthma | No | Min S, Lag 1 | Lag 1 | No |

S, LOESS smooth with a 50% span. Lag 0 refers to the same day as the event. Lag 1 refers to the previous day and so on. A term for day-of-week and seasonality (LOESS smoother with a 3-day span) was included in all models.

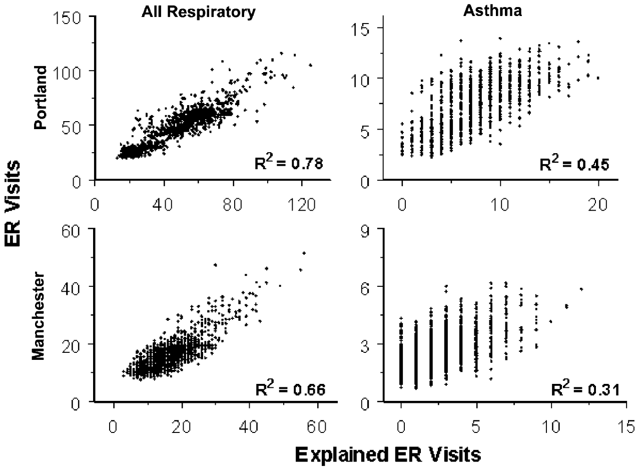

Fig. 5. Scatter plots of explained ER visits vs. actual ER visits. Explained ER visits are visits the models can explain using terms described in Table 3, with the addition of the 24-h average $SO_2$ value.

associated with a 5% (95% CI 2–7%) increase in all respiratory visits and a 6% (95% CI 1–12%) increase in asthma visits. These effects are evident at levels far below the EPA NAAQS of a 24-h average of 140 ppbv.

In Manchester, no significant relationships were revealed by this analysis, though two tend toward significance. The relative risk for pediatric asthma visits was close to significant with an estimate of 11% increase (95% CI 2–25%). Manchester all respiratory visits of people 65+ years old increased 4% (95% CI 3–11%).

Single pollutant models for $O_3$ also revealed a significant association (Fig. 8). Since $O_3$ was only collected in the spring–summer months (typically April–September), all models including $O_3$ are restricted to those months. Limiting the analysis to summer months led to no significant change in relative risk estimates. In Portland, $O_3$ is associated with a 5% (95% CI 1–10%) increase in asthma ER visits. Portland pediatric asthma visits were almost significant with a 7% (95% CI −2–17%). Ozone levels exceeded the NAAQS several times in both cities over the study period.

## 5. Conclusion

Elevated levels of $SO_2$ and $O_3$ were positively associated with elevated respiratory and asthmatic ER visits in the largest city, as defined by the HSA

Table 4
Summary of mean daily visits (95% confidence intervals) between type of ER visit, city, and age group

| | All respiratory | | Asthma | |
|---|---|---|---|---|
| | Portland | Manchester | Portland | Manchester |
| All ages | 49.0 (47.9–50.2) | 16.6 (16.3–16.9) | 7.4 (7.2–7.6) | 2.6 (2.6–2.7) |
| 0–14 | 10.1 (9.8–10.4) | 3.7 (3.6–3.8) | 2.0 (1.9–2.1) | 0.5 (0.4–0.5) |
| 15–64 | 29.2 (28.5–29.9) | 11.7 (11.5–12.0) | 4.6 (4.4–4.7) | 2.1 (2.0–2.1) |
| 65+ | 9.7 (9.4–10.1) | 1.2 (1.1–1.2) | 0.8 (0.7–0.9) | 0.1 (0.08–0.12) |

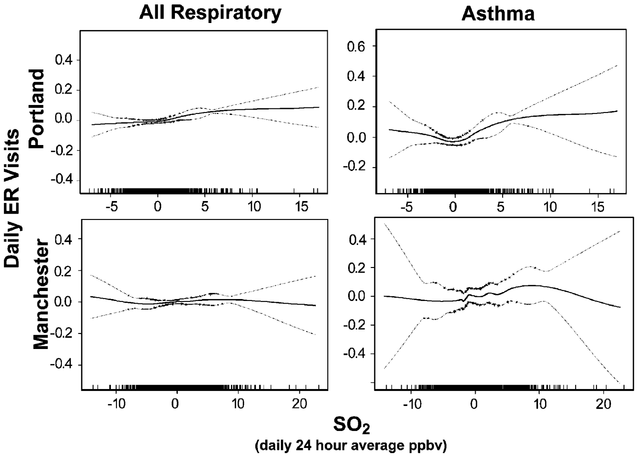

Fig. 6. Smoothed (LOESS 80% span) relationship between daily average $SO_2$ anomaly and ER visits for all respiratory reasons and asthma. Tick marks on bottom represent data distribution. Dashed lines are pointwise 95% confidence intervals. Both ER and $SO_2$ data have been filtered to remove confounding temporal variables.

population, in northern New England. High $SO_2$ days led to 5–10% increases in ER visits. An interquartile increase in $O_3$ led to a 5% increase in all aged asthma visits in Portland. The 65+ age group experienced an even greater increase in visits per day. The significance of these relationships is not sensitive to analytical or smoothing techniques. They cannot be explained by seasonal or other temporal patterns or weather, which were accounted for in the analysis. The lack of an association with gastroenteritis implies that the relationship between respiratory visits and air pollutants cannot be explained by changes in hospital administration or utilization patterns, or other city-wide risk factors. In Manchester, there were increases in ER visits associated with elevated pollution levels, but no relationships were statistically significant.

The associations reported in this study are of special interest for New England as much of its pollution, including $SO_2$ and $O_3$, is transported from sources in other upwind states (e.g., Cleveland et al., 1976; LeClair, 1997; New Hampshire Department of Environmental Services, 2004; Griffin et al., 2004; Mao and Talbot, 2004a, b). The presence of a detrimental effect of air pollution on human health suggests that pollution sources outside the region are responsible for health impacts within northern New England.

It is intriguing that significant relationships were found in Portland, but not Manchester. It is possible that ecological analysis is not an adequate tool for use in small cities because the smaller the signal in a time-series, the more difficult it is to isolate from the "noise." For example, imagine two cities, the first the size of New York, NY (population 19,011,000), and the second the size of Manchester, NH (population 176,000). With the national average of two ER asthma visits per 100,000 people per day, there would be a daily average of 380 visits in New York but only 3.5 visits in Manchester (Mannino et al., 2002). A 5% increase in daily visits due to air pollution would translate to an increase of 19 visits in the city the size of New York but only 0.18 visits in the city the size of Manchester. While the significance of the impact would be identical in the two cities, it would be much more difficult to identify in the smaller of the two. Another way to think about this issue is that a 0.3% increase due to air pollution would result in one additional visit to a New York emergency room, while it would take a 28% increase in Manchester to get the same. It is possible that the Manchester HSA has simply too small a population to identify statistically significant relationships between air pollution and air quality using city-wide, ecological time-series analysis. The Portland HSA was apparently sufficiently large. The difference in relative size of the two cities is apparent in Table 4. The Portland HSA generally has twice as many visits as the Manchester HAS. An additional complication for our analysis is that the pollutant burden with respect to the combustion of diesel and from other local sources of air pollution is probably different between the two cities.

Another remaining question for New England regards the possibility that other pollutants, such as $PM_{2.5}$, that covary somewhat with $SO_2$ ($R^2 = 0.20$) in Portland, but not in Manchester ($R^2 = 0.07$ over the period of record), may be responsible for the observed associations between ER visits and $SO_2$ (Fig. 9).

In Portland the relationship is much tighter; every high $SO_2$ day is accompanied by high $PM_{2.5}$. In Manchester the relationship is not as strong, though

Table 5
Relative risks for single pollutant ($SO_2$ and $O_3$) models for preadjusted predictor data

| Outcome | Age | $\beta$ | SE | *t* Value | IQR (75%–25%) | | | 10 μg/m$^3$ | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | RR | Lower CI | Upper CI | RR | Lower CI | Upper CI |
| *$SO_2$ Portland* | | | | | | | | | | |
| All respiratory | All | 0.007 | 0.002 | 4.045 | 1.05 | 1.02 | 1.07 | 1.03 | 1.01 | 1.04 |
| | 0–14 | −0.004 | 0.004 | −1.000 | 0.98 | 0.93 | 1.02 | 0.99 | 0.96 | 1.01 |
| | 15–64 | 0.009 | 0.002 | 4.066 | 1.06 | 1.03 | 1.09 | 1.04 | 1.02 | 1.05 |
| | 65+ | 0.015 | 0.004 | 3.725 | 1.10 | 1.05 | 1.15 | 1.06 | 1.03 | 1.09 |
| Asthma | All | 0.010 | 0.004 | 2.158 | 1.06 | 1.01 | 1.12 | 1.04 | 1.00 | 1.07 |
| | 0–14 | 0.005 | 0.009 | 0.604 | 1.03 | 0.93 | 1.15 | 1.02 | 0.95 | 1.09 |
| | 15–64 | 0.011 | 0.005 | 2.201 | 1.07 | 1.01 | 1.15 | 1.04 | 1.00 | 1.08 |
| | 65+ | 0.011 | 0.014 | 0.771 | 1.07 | 0.90 | 1.26 | 1.04 | 0.94 | 1.16 |
| *$SO_2$ Manchester* | | | | | | | | | | |
| All respiratory | All | 0.001 | 0.002 | 0.634 | 1.01 | 0.99 | 1.02 | 1.00 | 0.99 | 1.02 |
| | 0–14 | 0.000 | 0.004 | 0.042 | 1.00 | 0.96 | 1.04 | 1.00 | 0.97 | 1.03 |
| | 15–64 | 0.001 | 0.002 | 0.433 | 1.00 | 0.98 | 1.03 | 1.00 | 0.99 | 1.02 |
| | 65+ | 0.007 | 0.006 | 1.089 | 1.04 | 0.97 | 1.11 | 1.03 | 0.98 | 1.08 |
| Asthma | All | 0.006 | 0.005 | 1.240 | 1.03 | 0.98 | 1.09 | 1.02 | 0.99 | 1.06 |
| | 0–14 | 0.018 | 0.011 | 1.619 | 1.11 | 0.98 | 1.25 | 1.07 | 0.99 | 1.17 |
| | 15–64 | 0.003 | 0.006 | 0.545 | 1.02 | 0.96 | 1.08 | 1.01 | 0.97 | 1.05 |
| | 65+ | 0.011 | 0.023 | 0.459 | 1.06 | 0.83 | 1.36 | 1.04 | 0.88 | 1.24 |
| *$O_3$ Portland* | | | | | | | | | | |
| All respiratory | All | −0.001 | 0.001 | −1.214 | 0.99 | 0.97 | 1.01 | 1.00 | 0.99 | 1.00 |
| | 0–14 | −0.001 | 0.001 | −0.357 | 0.99 | 0.95 | 1.04 | 1.00 | 0.98 | 1.01 |
| | 15–64 | 0.000 | 0.001 | 0.000 | 1.00 | 0.98 | 1.02 | 1.00 | 0.99 | 1.01 |
| | 65+ | −0.002 | 0.001 | −1.672 | 0.97 | 0.93 | 1.01 | 0.99 | 0.98 | 1.00 |
| Asthma | All | 0.003 | 0.001 | 2.297 | 1.05 | 1.01 | 1.10 | 1.02 | 1.00 | 1.03 |
| | 0–14 | 0.004 | 0.003 | 1.471 | 1.07 | 0.98 | 1.17 | 1.02 | 0.99 | 1.05 |
| | 15–64 | −0.001 | 0.002 | −0.386 | 0.99 | 0.93 | 1.05 | 1.00 | 0.98 | 1.02 |
| | 65+ | −0.003 | 0.004 | −0.612 | 0.96 | 0.84 | 1.09 | 0.99 | 0.95 | 1.03 |
| *$O_3$ Manchester* | | | | | | | | | | |
| All respiratory | All | −0.001 | 0.001 | −0.900 | 0.98 | 0.95 | 1.02 | 1.00 | 0.99 | 1.01 |
| | 0–14 | 0.001 | 0.002 | 0.365 | 1.01 | 0.94 | 1.09 | 1.00 | 0.98 | 1.02 |
| | 15–64 | −0.001 | 0.001 | −1.000 | 0.98 | 0.95 | 1.02 | 0.99 | 0.99 | 1.00 |
| | 65+ | −0.004 | 0.004 | −0.900 | 0.94 | 0.81 | 1.08 | 0.98 | 0.94 | 1.02 |
| Asthma | All | −0.001 | 0.002 | −0.500 | 0.98 | 0.92 | 1.05 | 0.99 | 0.98 | 1.01 |
| | 0–14 | 0.002 | 0.006 | 0.349 | 1.04 | 0.85 | 1.26 | 1.01 | 0.95 | 1.07 |
| | 15–64 | −0.002 | 0.003 | −0.667 | 0.96 | 0.87 | 1.07 | 0.99 | 0.96 | 1.02 |
| | 65+ | NA | NA | | | | | | | |

$\beta$ linear regression coefficient from generalized additive model. SE, standard error of coefficient. *t* value, $\beta$/SE, a measure of significance. RR, relative risk. IQR, interquartile range, a change in pollution level from the 25th to the 75th percentile. NA, unstable estimates due to low counts of 65+ asthmatic visits combined with lack of year-round $O_3$ data.

there are less data available. This supports the hypothesis that the effects seen in this analysis may be due, in part or entirely, to $PM_{2.5}$. Unfortunately, fine particulate data have only been collected daily for only the past few years (since 2000 in Portland and 2001 in Manchester) which prevents detailed analysis of this possibility at this time. The lack of a more consistent association with ozone is also intriguing, as other researchers have found significant associations in cities with similar mean $O_3$ levels (Burnett et al., 2001; Weisel et al., 2002). Again, a significant effect was apparent in the larger of the two cities in this study. In summary, there is a significant increase in ER visits on days with elevated ozone and sulfur dioxide in Portland, Maine. However, $PM_{2.5}$ covaries somewhat with $SO_2$ and may be responsible for some or all of the observed association. In Manchester, no significant effects were found, though there were near-significant relationships. The lack of statistical significance may be due to the smaller population size of the city. While alone these findings are not definitive proof of a causal relationship, when this study is put into the context of the dozens of other studies on this topic in different places around the world, it is clear that elevated levels of some pollutants, even at levels below national standards, negatively affect public health.

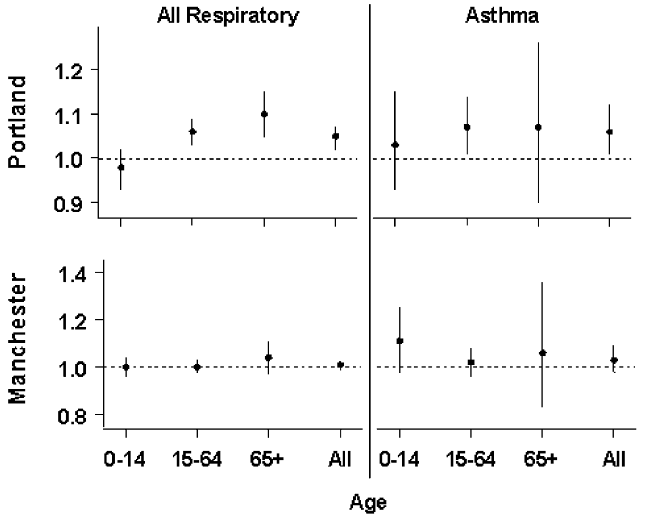

Fig. 7. Relative risk estimates (with 95% confidence intervals) for an interquartile increase in $SO_2$ in Portland, ME, and Manchester, NH.

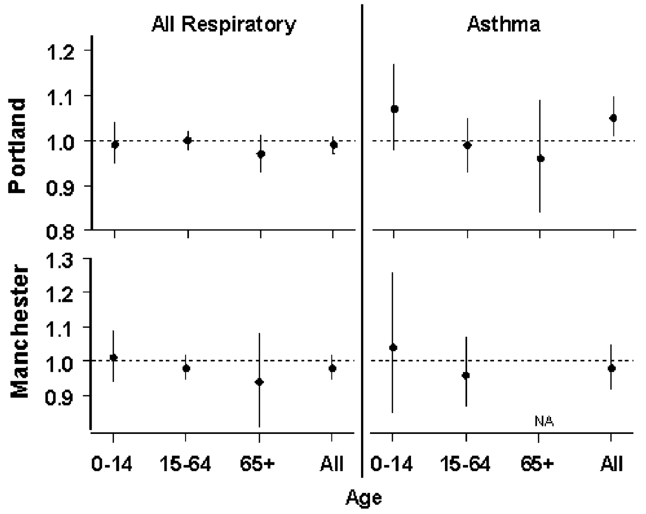

Fig. 8. Relative risk estimates (with 95% confidence intervals) for an interquartile increase in $O_3$ in Portland, ME, and Manchester, NH. NA, unstable estimates due to low counts of $65^+$ asthmatic visits combined with lack of year-round $O_3$ data.

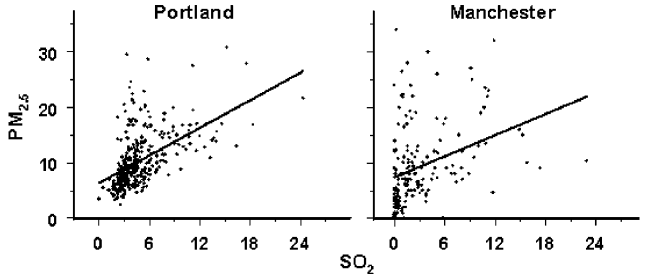

Fig. 9. Scatter plots of $PM_{2.5}$ (μg/m$^3$) versus $SO_2$ (ppbv) over the respective period of record for Portland, Maine, and Manchester, NH. Line is a least-squares regression.

Visits to the ER represent only a small percentage and most severe (i.e., the tip of the iceberg) of the total impacts of air pollution. Thurston has estimated that respiratory ER visits represent only about 0.1% of all adverse impact cases (Thurston, 1997). This places the results of ecological studies of ER visits in the context of much larger impacts of air pollution on public health. Epidemiological studies from diverse communities with unique air quality and weather phenomenon have determined that short-term variations in air quality are associated with negative effects on human health at the population level. By design, results from carefully conducted studies of this type should be considered conservative. In conjunction with the vast literature on controlled exposures, animal models, cohort studies, and cross-sectional studies, the evidence from time-series studies strongly suggests that there is a causal relationship between short-term exposure to air pollution and severe health problems (Holgate, 1999; Brunekreef and Holgate, 2002).

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