Short term effects of particulate matter on cause specific mortality: effects of lags and modification by city characteristics

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Background: Consistent evidence has shown increased all-cause mortality, and mortality from broad categories of causes associated with airborne particles. Less is known about associations with specific causes of death, and modifiers of those associations.

Aims: To examine these questions in 20 US cities, between 1989 and 2000.

Methods: Mortality files were obtained from the National Center for Health Statistics. Air pollution data were obtained from the Environmental Protection Agency website. The associations between daily concentrations of particulate matter of aero-diameter ≤ 10 μm (PM$_{10}$) and daily mortality from all-cause and selected causes of death, were examined using a case-crossover design. Temporal effects of PM$_{10}$ were examined using lag models, in first stage regressions. City specific modifiers of these associations were examined in second stage regressions.

Results: All-cause mortality increased with PM$_{10}$ exposures occurring both one and two days prior the event. Deaths from heart disease were primarily associated with PM$_{10}$ on the two days before, while respiratory deaths were associated with PM$_{10}$ exposure on all three days. Analyses using only one lag underestimated the effects for all-cause, heart, and respiratory deaths. Several city characteristics modified the effects of PM$_{10}$ on daily mortality. Important findings were seen for population density, percentage of primary PM$_{10}$ from traffic, variance of summer temperature, and mean of winter temperature.

Conclusions: There was overall evidence of increased daily mortality from increased concentrations of PM$_{10}$ that persisted across several days, and matching for temperature did not affect these associations. Heterogeneity in the city specific PM$_{10}$ effects could be explained by differences in certain city characteristics.
We used publicly available sources to obtain air pollution data and weather data for the same time period. A case-crossover design analysis was used to evaluate the acute effects of daily PM$_{10}$ concentrations on mortality. Short term effects of particulate matter on daily mortality were examined using lag models. Several studies have examined factors that may explain heterogeneity in the effects of PM$_{10}$ by location (city).\textsuperscript{6, 7} In our study we examined the potential for effect modification of the PM$_{10}$—daily mortality estimates by city characteristics, specifically the prevalence of central air conditioning, population density, standardized mortality rates, the proportion of elderly in each city, daily minimum temperature, temperature in summer (mean and variance), daily maximum apparent temperature in winter (mean and variance), and percentage of primary PM$_{10}$ from traffic sources.

**METHODS**

The study included a period of 12 years between 1 January 1989 and 31 December 2000. We selected 20 cities in the United States with sufficient mortality and daily air pollution data: Birmingham, Alabama; Boulder, Colorado; Canton, Ohio; Chicago, Illinois; Cincinnati, Ohio; Cleveland, Ohio; Colorado Springs, Colorado; Columbus, Ohio; Denver, Colorado; Detroit, Michigan; Honolulu, Hawaii; Minneapolis, Minnesota; Nashville, Tennessee; New Haven, Connecticut; Pittsburgh, Pennsylvania; Provo, Utah; Salt Lake City, Utah; Seattle, Washington; Terra Haute, Indiana; and Youngstown, Ohio.

**Daily mortality**

Mortality files were obtained from the National Center for Health Statistics (NCHS) for the period between 1989 and 2000. The mortality files provided information on the exact date of death, and the underlying cause of death. For this study we selected all-cause daily mortality excluding any deaths from accidental causes (ICD code, 10th revision V01–Y98). Specific cause mortality case groups were derived from this previous group for the following underlying causes of death: heart disease (I01–151), ischaemic heart disease (IHD) (I20–125), myocardial infarction (MI) (I21, I22), dysrythmias (I46–I49), heart failure (HF) (I50), stroke (I60–I69), respiratory disease (J00–J99), pneumonia (J12–J18), and chronic obstructive pulmonary disease (COPD) (J40–J44, J47).

**Air pollution**

Data for PM$_{10}$ were obtained from the United States Environmental Protection Agency Aerometric Information Retrieval System (US EPA AIRS) for the same period of years.\textsuperscript{37} US EPA AIRS retrieves data from multiple monitors in each county for daily and hourly average measurements. The sampling method for hourly data uses monitors which are susceptible to a greater loss of semi-volatile particles from traffic, than the integrated 24 hour (daily) monitors. The hourly monitors heat the sample to 50°C to remove water from the mass, and in doing so it volatilises the semi-volatile PM components. Even more complicated is the fact that the amount of semi-volatile mass for a given sample in the hourly measurements will likely vary by location, season, and even time of day, thus requiring constant adjustments by a reference method. Therefore, the integrated method provided the highest quality data for our analysis.\textsuperscript{40, 41}

Air pollution data from multiple monitors in each city were used to estimate a common value for the city, using an averaging method based on an algorithm described previously by Schwartz.\textsuperscript{45} However, before applying this algorithm, we made sure that all monitors in one city represented general ambient exposures, and not rather a local source. For this, we calculated the correlation between city monitors. We obtained multiple correlation coefficients for each monitor (correlated with all other monitors in the city), from which we extracted the median values. Those monitors falling in the low 10th centile of the distribution of the median values, across all cities, were excluded from the analyses.

While we selected cities with daily PM$_{10}$ monitoring, daily concentrations of PM$_{10}$ were occasionally missing. Even small numbers of missing data can present a problem when examining multiple lags of exposure in a model. We used regression models to predict missing PM$_{10}$ daily values using local meteorological data obtained from the United States Surface Airways and Airways Solar Radiation hourly data (NESDIS) (including extinction coefficient,\textsuperscript{46} a measure of light scattering by fine particles), and the PM$_{10}$ concentration the day before and the day after. Prior to filling in the missing values, we made sure that we used only months missing less than 25% of the days, and PM$_{10}$ daily values equal or less than 300 µg/m$^3$.

**Statistical methods of analysis**

A case-crossover design was carried out to examine the association between daily mortality and PM$_{10}$. The approach, first described by Maclure,\textsuperscript{41} is similar in concept to a case-control study, except that now cases and controls are the same subject, but in different times. A case is defined by the time of the event (day of the event in our case), and controls are chosen as the times (days) free of the event, selected to be close to the event day in time. Bateson and Schwartz showed that such matching can control even strong confounding by season and time trends.\textsuperscript{42, 43} We chose these control days by using a time stratified approach.\textsuperscript{44} This involves choosing control days to be all other days (or a sample of all other days) of a fixed time strata, typically the same month of the same year as the event. Using monthly strata has been shown to produce unbiased estimates of effect sizes and coverage probabilities even in the presence of strong seasonal confounding.\textsuperscript{45} Control days have different exposures from that of the case, since exposures change from day to day. As in a matched case-control study, conditional logistic regression is applied to the matched pairs to compare different characteristics between the case day (day of the event) and its control days (days free of the event), including exposure characteristics. Because of its design, the case-crossover approach controls for factors that change slowly over time,\textsuperscript{42, 43} or factors that are individual characteristics which may, in another case, be potential confounders.\textsuperscript{41} In our study, controls were selected within the month of the event, leaving two days between each control day to eliminate any serial correlation.

The statistical modelling involved two hierarchical stages. Effects of PM$_{10}$ on daily mortality were first estimated through city specific models, in the first stage analyses. Risk of mortality was evaluated in association with PM$_{10}$ exposure concentrations on the same day of the event (lag 0), one (lag 1), and two days (lag 2) prior the event. The models included one lag at a time (single lag models), or all three lags. The latter is described as a “distributed lag model” and is a way to estimate unbiased time trends of the exposure-response relation, by controlling for confounding in exposure effects in one lag by exposures in other lags.\textsuperscript{46} All models included “day of week” as indicator variables, and quadratic spline functions for apparent temperature (AT) on the same day and the day before death, to control for effect of weather.\textsuperscript{47, 48} In the form: $AT_{ij}$ + $AT_{ij}^2$ + ($AT_{ij}$ – city specific mean $AT_{ij}$)$^2$, where i represents city, and j represents lag of AT. Given the humidity, AT is defined as the perceived body temperature, and was calculated as: $AT = -2.653 + (0.9947Ta) +$
Table 1  Characteristics* of the 20 cities in the United States included in the study of the association between PM$_{10}$ and daily mortality, between 1989 and 2000

<table>
<thead>
<tr>
<th>City</th>
<th>Population density†</th>
<th>% central AC‡</th>
<th>Minimum summer AT (SD) (°C)</th>
<th>Minimum winter AT (SD) (°C)</th>
<th>Mean PM$_{10}$ (SD) (µg/m$^3$)</th>
<th>% of primary PM$_{10}$ from traffic</th>
<th>Standardised mortality rates*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Birmingham, Alabama</td>
<td>422</td>
<td>70.2</td>
<td>29.3 (3.3)</td>
<td>6.7 (5.8)</td>
<td>31.9 (18.0)</td>
<td>1.5</td>
<td>0.0107</td>
</tr>
<tr>
<td>Boulder, Colorado</td>
<td>393</td>
<td>6.3</td>
<td>20.1 (3.3)</td>
<td>-1.2 (5.4)</td>
<td>22.1 (11.3)</td>
<td>1.7</td>
<td>0.0066</td>
</tr>
<tr>
<td>Canton, Ohio</td>
<td>656</td>
<td>30</td>
<td>22.5 (4.6)</td>
<td>-3.0 (5.5)</td>
<td>26.6 (11.5)</td>
<td>3.0</td>
<td>0.0098</td>
</tr>
<tr>
<td>Chicago, Illinois</td>
<td>5684</td>
<td>43.2</td>
<td>23.6 (5.3)</td>
<td>-3.5 (4.9)</td>
<td>33.7 (16.4)</td>
<td>5.0</td>
<td>0.0077</td>
</tr>
<tr>
<td>Cincinnati, Ohio</td>
<td>2077</td>
<td>66.2</td>
<td>25.1 (4.5)</td>
<td>-0.5 (6.0)</td>
<td>31.4 (13.9)</td>
<td>2.8</td>
<td>0.0083</td>
</tr>
<tr>
<td>Cleveland, Ohio</td>
<td>3044</td>
<td>39.3</td>
<td>23.2 (4.8)</td>
<td>-2.2 (5.7)</td>
<td>37.5 (18.7)</td>
<td>4.8</td>
<td>0.0064</td>
</tr>
<tr>
<td>Colorado Springs, Colorado</td>
<td>243</td>
<td>13.4</td>
<td>18.3 (5.6)</td>
<td>-0.9 (5.3)</td>
<td>24.0 (13.2)</td>
<td>1.6</td>
<td>0.0086</td>
</tr>
<tr>
<td>Columbus, Ohio</td>
<td>1980</td>
<td>63.7</td>
<td>24.6 (4.7)</td>
<td>-1.4 (4.7)</td>
<td>28.5 (12.5)</td>
<td>3.0</td>
<td>0.0127</td>
</tr>
<tr>
<td>Denver, Colorado</td>
<td>3625</td>
<td>25.7</td>
<td>20.1 (3.6)</td>
<td>-0.9 (5.6)</td>
<td>28.5 (12.8)</td>
<td>3.0</td>
<td>0.0094</td>
</tr>
<tr>
<td>Detroit, Michigan</td>
<td>3357</td>
<td>41</td>
<td>23.2 (4.9)</td>
<td>-3.1 (4.4)</td>
<td>32.1 (17.7)</td>
<td>7.5</td>
<td>0.0086</td>
</tr>
<tr>
<td>Honolulu, Hawaii</td>
<td>1460</td>
<td>-</td>
<td>29.0 (1.3)</td>
<td>24.9 (1.9)</td>
<td>15.9 (6.8)</td>
<td>2.8</td>
<td>0.0079</td>
</tr>
<tr>
<td>Minneapolis, Minnesota</td>
<td>2282</td>
<td>48.4</td>
<td>22.3 (4.9)</td>
<td>-6.6 (4.5)</td>
<td>24.7 (12.3)</td>
<td>4.2</td>
<td>0.0096</td>
</tr>
<tr>
<td>Nashville, Tennessee</td>
<td>1135</td>
<td>72.2</td>
<td>28.7 (3.8)</td>
<td>3.8 (6.0)</td>
<td>30.1 (12.1)</td>
<td>2.5</td>
<td>0.0112</td>
</tr>
<tr>
<td>New Haven, Connecticut</td>
<td>1360</td>
<td>23.9</td>
<td>23.1 (4.6)</td>
<td>-2.0 (4.2)</td>
<td>25.4 (14.4)</td>
<td>5.6</td>
<td>0.0104</td>
</tr>
<tr>
<td>Pittsburgh, Pennsylvania</td>
<td>1756</td>
<td>33.4</td>
<td>23.3 (4.4)</td>
<td>-1.5 (5.3)</td>
<td>30.2 (18.5)</td>
<td>5.0</td>
<td>0.0090</td>
</tr>
<tr>
<td>Provo, Utah</td>
<td>185</td>
<td>26.9</td>
<td>22.4 (4.3)</td>
<td>-2.0 (4.1)</td>
<td>33.7 (22.2)</td>
<td>2.2</td>
<td>0.0098</td>
</tr>
<tr>
<td>Seattle, Washington</td>
<td>817</td>
<td>6.2</td>
<td>17.0 (3.6)</td>
<td>3.1 (3.5)</td>
<td>22.4 (14.7)</td>
<td>2.8</td>
<td>0.0130</td>
</tr>
<tr>
<td>Salt Lake City, Utah</td>
<td>1219</td>
<td>39.7</td>
<td>22.4 (4.4)</td>
<td>-2.1 (4.1)</td>
<td>35.0 (20.8)</td>
<td>3.0</td>
<td>0.0082</td>
</tr>
<tr>
<td>Terra Haute, Indiana</td>
<td>262</td>
<td>71.6</td>
<td>24.8 (4.4)</td>
<td>-3.6 (5.4)</td>
<td>29.2 (14.6)</td>
<td>1.9</td>
<td>0.0075</td>
</tr>
<tr>
<td>Youngstown, Ohio</td>
<td>390</td>
<td>22.8</td>
<td>22.1 (4.7)</td>
<td>-2.9 (4.8)</td>
<td>30.8 (13.9)</td>
<td>2.9</td>
<td>0.0077</td>
</tr>
</tbody>
</table>

AC, air conditioning; AT, apparent temperature; PM$_{10}$, particulate matter of aerodynamic diameter equal or less than 10 µm; SD, standard deviation.
†All descriptive statistics for weather and PM$_{10}$ concentrations were extracted from the available data between 1989 and 2000.
‡United States Census 2000 data (count/mile$^2$).
§American Housing Survey (AHS), United States Census Bureau, between 1994 and 2000. Data for Honolulu, HI are missing due to no available data after 1983 from the AHS.
||Data obtained from the United States Environmental Protection Agency website: www.epa.gov/ttn/.
*Age standardised mortality rates were computed using United States population as the standard population, retrieved from the 2000 Census Data.

(0.0153 Td$^2$), where Ta is air temperature and Td is dew point temperature. The overall variance was computed as:

$$Var\left(\sum \beta_i\right) = Var\left(\beta_0\right) + \sum Cov\left(\beta_j\right),$$

where $\beta_0$ is the city-specific lag-specific slope, i represents city, and j = 0, 1, 2 defines lag.

In the second stage analyses, maximum likelihood meta-regression models estimated summary effects for mortality causes and PM$_{10}$ associations across the 20 cities, allowing...
for heterogeneity in city specific response using a random effect model.\textsuperscript{52}

**Effect modification**

We examined the potential for effect modification of the cumulative PM\textsubscript{10}-mortality estimates by city characteristics including the prevalence of central air conditioning, population density, standardised mortality rates, the proportion of elderly in each city (greater than 65, 75, or 85 years old), daily minimum apparent temperature (mean and variance) in summer (June, July, August), daily maximum apparent temperature (mean and variance) in winter (December, January, February), and percentage of primary PM\textsubscript{10} from traffic sources. These factors were examined in the second stage random meta-regressions.\textsuperscript{53} \textsuperscript{54} \textsuperscript{55} \textsuperscript{56}

The estimates of PM\textsubscript{10}-mortality association reported in this paper refer to percentage increase in mortality per any 10 \textmu g/m\textsuperscript{3} increment of PM\textsubscript{10} concentration. SAS statistical software package was used for all data management, and statistical analyses of the first stage. S-plus was used to implement the Berkey method for random meta-regression analyses.\textsuperscript{51}

**RESULTS**

The 20 selected cities showed variability in the city-specific characteristics (table 1). In several cities, the higher population density corresponded well with higher percentage of primary PM\textsubscript{10} from traffic sources, suggesting highly urbanised areas. Some cities had relatively high percentages of central air conditioning including Birmingham, Cincinnati, Columbus, Nashville, and Terra Haute, which was also consistent with higher summer AT. Overall mean concentration of PM\textsubscript{10} varied by city and across time within city. Birmingham, Cleveland, Provo, and Salt Lake City had higher and more variable concentrations of daily PM\textsubscript{10}.

Average annual mortality events per 100 000 were higher in Birmingham, Minneapolis, Nashville, Pittsburgh, and Terra Haute. Mortality from any respiratory disease was about 10\% of all-cause mortality (table 2), and of these, 40–50\% were deaths from chronic obstructive pulmonary disease (COPD), and about 35\% were deaths from pneumonia. One third of all deaths were from heart disease, the majority of which were ischaemic heart disease (IHD) (70\%), and in small proportions heart failure (HF) (6\%), and dysrhythmias (6\%). Almost half of ischaemic heart disease mortality cases were diagnosed as acute myocardial infarction (MI). Mortality from stroke was about 7\% of all-cause mortality (table 2). In total, we studied 1 896 306 deaths.

Single lag model results showed, in general, increased risk of mortality with concentrations of PM\textsubscript{10} the day before and two days before of the event (lags 1 and 2) (table 3). Because of the potential bias due to confounding from exposures in other days, the results from the unconstrained distributed lag models presented more valid estimates of the distribution of the effects of PM\textsubscript{10} over time (table 3). All-cause mortality increased with increasing concentrations of PM\textsubscript{10} the day before and two days before the event, with effects essentially zero on the same day. When we examined broad categories of mortality causes, we saw different patterns. Respiratory mortality effects were distributed over all three lags. In contrast, cardiac deaths were associated with exposure the day before and two days before the death. The more specific causes had more mixed patterns, but the standard errors of the effect estimates for these rarer outcomes were large, limiting interpretation of the distributed lag pattern. Interesting to note was the strong positive association for mortality from heart failure with concentrations two days prior the event.

The cumulative increase for all-cause mortality due to PM\textsubscript{10} concentrations across the three days was 0.45\%, which was about a quarter more than what was seen with the strongest single day lag. All respiratory mortality increased 0.87\% across the three days. The largest impact of PM\textsubscript{10} concentrations in these three days was on the deaths from pneumonia (1.24\%). Deaths from any heart disease showed a 0.50\% increase. The cumulative increase for IHD over the three days was somewhat greater than for all heart disease mortality. Mortality from stroke showed a 0.46\% relative increase, although imprecisely estimated.

Matching on AT resulted in less power, thus it was difficult to interpret the results for cause specific mortality. However, the effects on all-cause mortality did show a similar pattern with the results of models that had included AT as a covariate. Overall, the estimate for all-cause mortality was 0.52\% (95\% CI 0.31\% to 0.72\%).

We found no great impact of city-level characteristics on the overall estimates of PM\textsubscript{10}—cause specific mortality, although power was weak for cause specific deaths. However, we observed differences in the PM\textsubscript{10} effects for all-cause mortality for several of these characteristics (table 4). Percentage increase in daily mortality was higher for denser populated areas (90\% greater comparing locations with 3000 persons/mile\textsuperscript{2} to locations with 1000 persons/mile\textsuperscript{2}), and higher for those cities with a higher fraction of primary PM\textsubscript{10} from traffic (threefold comparing the estimate for the 75th centile with that of the 25th centile of the distribution). Higher variability in summer apparent temperature was associated with a greater impact of PM\textsubscript{10} (about sixfold for the comparison of the interquartile range, 25th to 75th centile), as were lower winter temperatures (44\% increase comparing the 75th and 25th centiles of the distribution). These important findings are also illustrated in fig 1. There was an indication that a greater proportion of the elderly in the city also modified the effect of PM\textsubscript{10} on daily mortality (proportion of those older than 65 or 75 years, with the difference between the first and third quartiles being 56\% and 51\% respectively) (table 4).

**DISCUSSION**

In a large, multi-city study, we examined the effects of PM\textsubscript{10} on daily mortality across three days: on the day of the event (death), and one and two days before, using a case-crossover design. We observed increased all-cause mortality for increasing concentrations of PM\textsubscript{10} on the day before and two days before the event.

Some previous studies have been criticised for reporting the PM\textsubscript{10} effects on mortality for the exposure lag showing the strongest association. It has been argued that this overestimates the effect of exposure. However, we found that considering the multi-day effects increased our estimates of the short term effects of PM\textsubscript{10} on all-cause mortality by about one quarter, compared to even the strongest lag. This finding is important for risk assessment, suggesting that effect estimates from studies that used a single day rather than a distributed lag exposure, will be lower. The effect of PM\textsubscript{10} on mortality from respiratory causes persisted in all three days. This was also true for pneumonia deaths, whereas deaths from COPD were predominantly associated with PM\textsubscript{10} concentrations the two days before. Deaths from all heart disease showed association primarily with concentrations of PM\textsubscript{10} the two days before (lags 1 and 2). However, mortality from myocardial infarction was only associated with concentrations on the same day. We found a larger, but imprecise association with heart failure deaths. Stroke daily deaths were mainly associated with the day before concentrations (lag 1), although imprecisely estimated. Because of insufficient power, we could not make stronger conclusions.
### Table 3

<table>
<thead>
<tr>
<th>Mortality causes</th>
<th>3-day cumulative estimates</th>
<th>Percentage increase</th>
<th>% 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single lag model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lag 0</td>
<td>Lag 1</td>
<td>Lag 2</td>
<td></td>
</tr>
<tr>
<td>0.04 to 0.20</td>
<td>0.33</td>
<td>0.19 to 0.47</td>
<td></td>
</tr>
<tr>
<td><strong>Respiratory disease</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.08 to 1.09</td>
<td>0.59</td>
<td>0.42 to 0.76</td>
<td></td>
</tr>
<tr>
<td><strong>COPD</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.06 to 1.00</td>
<td>0.39</td>
<td>0.24 to 0.54</td>
<td></td>
</tr>
<tr>
<td><strong>Pneumonia</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.09 to 1.10</td>
<td>0.63</td>
<td>0.47 to 0.82</td>
<td></td>
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<tr>
<td><strong>Heart disease</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.06 to 0.30</td>
<td>0.23</td>
<td>0.13 to 0.34</td>
<td></td>
</tr>
<tr>
<td><strong>IHD</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.03 to 0.41</td>
<td>0.24</td>
<td>0.15 to 0.34</td>
<td></td>
</tr>
<tr>
<td><strong>MI</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.02 to 0.22</td>
<td>0.14</td>
<td>0.08 to 0.21</td>
<td></td>
</tr>
<tr>
<td><strong>HF</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.01 to 0.06</td>
<td>0.03</td>
<td>0.01 to 0.08</td>
<td></td>
</tr>
<tr>
<td><strong>Stroke</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.04 to 0.54</td>
<td>0.34</td>
<td>0.21 to 0.49</td>
<td></td>
</tr>
</tbody>
</table>

The persistent PM$_{10}$ effects for respiratory mortality, and in particular pneumonia deaths supported epidemiological findings for an exacerbation of inflammation in immunocompromised subjects. Zelikoff and colleagues suggested that PM$_{10}$ may act as an immunosuppressive agent which can disrupt normal pulmonary antimicrobial defence mechanisms, and illustrated this in animal models. They showed that even single exposures to ambient particulate matter are able to compromise normal recovery mechanisms. The findings for myocardial infarction were consistent with the suggested mechanisms for exposure related triggering of coronary events within 24 hours. We confirmed the reports of Hock and colleagues and Goldberg and colleagues that heart failure appears a particularly sensitive outcome. However, those previous studies could only investigate single locations. We also provided suggestive evidence that mortality from stroke was associated with PM$_{10}$ in the United States. This has been previously only reported in Asian populations.

We have also confirmed the findings reported in a more limited study by Schwartz, that choosing control days matched to the same temperature as the event days, did not change the PM$_{10}$ effects. This indicates that the observed PM$_{10}$-mortality associations were unlikely to be due to temperature confounding.

We considered the hypothesis that heterogeneity in the city PM$_{10}$ effects could be due to certain city sociodemographic, physical, and environmental characteristics. The study of Janssen et al had reported differing of the PM$_{10}$ effects on cardiovascular hospital admissions due to differences in the proportion of central air conditioning in each city. They also observed important difference by source of primary PM$_{10}$, with traffic sources showing a greater effect, suggesting higher toxicity. Another study by Katsouyanni and colleagues looked at several groups of such city characteristics. They reported a higher effect of PM$_{10}$ on mortality in cities with a lower ratio of PM$_{10}$ to nitrogen dioxide (NO$_2$) in the pollution mix, higher mean daily temperature, lower mean relative humidity, lower standard mortality rates, and higher proportion of susceptibles (age 65 years or older).

We found densely populated cities to have a greater effect of PM$_{10}$ on daily mortality. We hypothesised that there were two reasons why denser cities had more daily deaths due to air pollution exposure. First, there may be a greater toxicity of the source particles, or, second, the population in denser cities may be more susceptible. Denser populated cities, in general, tend to be more urban, and thus a larger percentage of the primary PM$_{10}$ is from traffic sources. The finding we obtained for percentage of primary PM$_{10}$ from traffic corroborated this hypothesis. These results corresponded well
with results of Laden and colleagues, who found greater toxicity from traffic particles in a source apportionment study. This is also broadly consistent with the results of Katsouyanni and colleagues. The lower ratio of PM$_{10}$ to NO$_2$, which modified the particle effect in that study, could be interpreted as indicating a city with a larger proportion of particles from traffic, which generates most of the NO$_2$ in urban areas. It may also explain the lower effect size estimates reported from Eastern Europe, where coal combustion accounts for a much larger proportion of the PM$_{10}$ to NO$_2$, which modified the particle effect in that study.

The second hypothesis, that such a difference in effects could be due to a more susceptible population in denser cities, was only partly supported when examining the age distribution in our study, as well as when examining the potential for modifying the PM$_{10}$ effects of age standardised mortality rates, and the proportion of those greater than 65, 75, or 85 years old, in each city. Katsouyanni and colleagues had seen the greater effect of PM$_{10}$ in cities with lower age standardised mortality rates, and with higher proportion of older ages (greater than 65 years). No modifying effect of age standardised mortality rates was seen in our study. However, the study findings suggested that a greater impact of PM$_{10}$ concentrations was present in cities with a larger proportion of those older than 65 or 75 years.

A new observation of ours was a higher effect of PM$_{10}$ in cities with greater summer temperature variability. High variability in temperature may be related to exposure differences, as more days with open windows may occur in the summer time in cities with such variability, compared to cities that are consistently hot in the summer, where continual air conditioning use is more common. Higher ventilation is associated with a steeper slope of the association between personal exposure to particles and ambient concentrations. The finding of a higher effect of PM$_{10}$ in Mediterranean cities in the multicentre European study of air pollution (APHEA II) may reflect the same exposure phenomena, as air conditioning is rare in those cities, and high ventilation rates are the norm in the summer. Alternatively, this modification may result from some interaction between temperature exposure and exposure to air pollution. However, Samet and coworkers did not observe any interaction between temperature and air pollution in Philadelphia. Cooler winter temperatures are associated with increased mortality risk; they also appeared to modify the effects of air pollution in our study.

We note that some city characteristics may vary over a 12 year period, and we were limited on this by data availability. However, population density, and apparent temperature may not, on average, vary by much in a 12 year period.

Most of the specific groups of diseases examined in this study are strongly influenced by other risk factors, such as individual social habits (smoking and drinking), and individual characteristics. In our study, we controlled for this by design, using a case-crossover sampling. In such study each case serves as its control on the event-free days. This

![Figure 1: Effect modification by city characteristics in the 20 cities in the United States, between 1989 and 2000. AT, apparent temperature; PM$_{10}$, particulate matter of aerodynamic diameter <10 μm. The two estimates and their 95% CI for each of the modifying factors represent the percentage increase in mortality for any 10 μg/m$^3$ of PM$_{10}$, for the 25th centile, and 75th centile of the modifier distribution across the 20 cities. For population density, the percentage increase in mortality per 1000 count/mile$^2$ of PM$_{10}$ is presented for 1000 count/mile$^2$, and 3000 count/mile$^2$.](http://oem.bmj.com/)

| Table 4: Modification of “all-cause” daily mortality; PM$_{10}$ association by city characteristics* across 20 cities in the United States, between 1989 and 2000 |

<table>
<thead>
<tr>
<th>City characteristics</th>
<th>Effect modifier coefficient†</th>
<th>% increase at the 25th centile‡</th>
<th>% increase at the 75th centile§</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Central air conditioning</td>
<td>-0.13 to -1.42, 1.15</td>
<td>24.8, 0.45, 0.17 to 0.72</td>
<td>56.1, 0.41, 0.11 to 0.70</td>
</tr>
<tr>
<td>Population density (count/mile$^2$)</td>
<td>0.12 to 0.04, 0.20</td>
<td>1000, 0.27, 0.04 to 0.49</td>
<td>3000, 0.51, 0.38 to 0.63</td>
</tr>
<tr>
<td>Age standardised mortality rate</td>
<td>-2.55 to -19.88, 0.008</td>
<td>0.47, 0.17 to 0.80, 0.010, 0.41, 0.17 to 0.66</td>
<td></td>
</tr>
<tr>
<td>% &gt;65 years old</td>
<td>0.05 to -0.01, 0.11</td>
<td>10.3, 0.34, 0.11 to 0.58</td>
<td>14.3, 0.53, 0.33 to 0.74</td>
</tr>
<tr>
<td>% &gt;75 years old</td>
<td>0.08 to -0.04, 0.20</td>
<td>5.1, 0.36, 0.12 to 0.59</td>
<td>7.3, 0.54, 0.32 to 0.76</td>
</tr>
<tr>
<td>% &gt;85 years old</td>
<td>0.22 to -0.28, 0.71</td>
<td>1.3, 0.37, 0.13 to 0.62</td>
<td>1.8, 0.49, 0.27 to 0.72</td>
</tr>
<tr>
<td>Daily minimum summer AT (°C)</td>
<td>-0.01 to -0.09, 0.06</td>
<td>22.3, 0.45, 0.16 to 0.74</td>
<td>24.7, 0.41, 0.09 to 0.73</td>
</tr>
<tr>
<td>Variance</td>
<td>0.41 to 0.14, 0.67</td>
<td>3.6, 0.09, -0.23 to 0.40</td>
<td>4.7, 0.52, 0.37 to 0.67</td>
</tr>
<tr>
<td>Daily maximum winter AT (°C)</td>
<td>-0.086 to -0.14, -0.03</td>
<td>-2.9, 0.59, 0.43 to 0.75</td>
<td>-0.8, 0.41, 0.25 to 0.58</td>
</tr>
<tr>
<td>Variance</td>
<td>0.10 to -0.16, 0.36</td>
<td>4.4, 0.40, 0.17 to 0.62</td>
<td>5.5, 0.51, 0.25 to 0.76</td>
</tr>
<tr>
<td>% of primary PM$_{10}$ from traffic</td>
<td>0.168 to 0.06, 0.26</td>
<td>2.4, 0.15, -0.11 to 0.42</td>
<td>4.4, 0.46, 0.31 to 0.61</td>
</tr>
</tbody>
</table>

PM$_{10}$, particulate matter of aerodynamic diameter <10 μm.

*Effect modification by city characteristics was examined for the three-day cumulative effect for “all-cause” mortality.

†The estimates represent the coefficient of the interaction term for the tested modifier on the mortality-PM$_{10}$ association. The estimates for the city effect modifiers are presented as percentage increase in mortality per 10 μg/m$^3$ increase in PM$_{10}$ per every unit increase in the modifier as shown in the table. The estimate for population density is presented as percent increase in mortality per each increment of 10 μg/m$^3$ of PM$_{10}$ per 1000 count/mile$^2$.

‡The estimates are presented as percentage increase in mortality per 10 μg/m$^3$ of PM$_{10}$ for the 25th centile and 75th centile of the distribution of city effect modifiers. For population density, the estimates are presented as percentage increase in mortality per 10 μg/m$^3$ of PM$_{10}$ for 1000 count/mile$^2$ and 3000 count/mile$^2$.

§Significant at $\alpha=0.05$.
Main messages

- Particulate matter has been associated with short term increases in morbidity and mortality.
- The study found increased all-cause, respiratory, and heart disease mortality in association with particulate matter of aerodynamic diameter <10 μm (PM$_{10}$), with effects being persistent over several days. Matching control days on temperature did not change this association.
- Several city characteristics modified the effects of PM$_{10}$ on daily mortality, notably the percentage of particles from traffic.

Policy implications

- Reducing levels of particulate matter may contribute to reducing mortality associated with it.
- Attention must be paid to traffic related air pollution, as suggestive of higher toxicity.

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9 Schwartz J. What are people dying of at high air pollution days? Environ Res 1994;64:26–35.


Short term effects of particulate matter on cause specific mortality: effects of lags and modification by city characteristics
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