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Kazuhiko Ito
New York University

Robert Mathes
New York City Department of Health and Mental Hygiene

Zev Ross
ZevRoss Spatial Analysis

Arthur Nádas
New York University

George Thurston
New York University

See next page for additional authors

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Authors
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Kazuhiko Ito,1 Robert Mathes,2 Zev Ross,3 Arthur Nádas,1 George Thurston,1 and Thomas Matte4

1New York University School of Medicine, Tuxedo, New York, USA; 2New York City Department of Health and Mental Hygiene, New York, New York, USA; 3ZevRoss Spatial Analysis, Ithaca, New York, USA; 4Hunter College, City University of New York School of Public Health, New York, New York, USA

BACKGROUND: Recent time-series studies have indicated that both cardiovascular disease (CVD) mortality and hospitalizations are associated with particulate matter (PM). However, seasonal patterns of PM associations with these outcomes are not consistent, and PM components responsible for these associations have not been determined. We investigated this issue in New York City (NYC), where PM originates from regional and local combustion sources.

OBJECTIVE: In this study, we examined the role of particulate matter with aerodynamic diameter ≤ 2.5 µm (PM2.5) and its key chemical components on both CVD hospitalizations and on mortality in NYC.

METHODS: We analyzed daily deaths and emergency hospitalizations for CVDs among persons ≥ 40 years of age for associations with PM2.5, its chemical components, nitrogen dioxide (NO2), carbon monoxide, and sulfur dioxide for the years 2000–2006 using a Poisson time-series model adjusting for temporal and seasonal trends, temperature effects, and day of the week. We estimated excess risks per interquartile-range increase at lags 0 through 3 days for warm (April through September) and cold (October through March) seasons.

RESULTS: The CVD mortality series exhibit strong seasonal trends, whereas the CVD hospitalization series show a strong day-of-week pattern. These outcome series were not correlated with each other but were individually associated with a number of PM2.5 chemical components from regional and local sources, each with different seasonal patterns and lags. Coal-combustion–related components (e.g., selenium) were associated with CVD mortality in summer and CVD hospitalizations in winter, whereas elemental carbon and NO2 showed associations with these outcomes in both seasons.

CONCLUSION: Local combustion sources, including traffic and residual oil burning, may play a year-round role in the associations between air pollution and CVD outcomes, but transported aerosols may explain the seasonal variation in associations shown by PM2.5 mass.


Recent reviews of the health effects of particulate matter (PM) air pollution suggest evidence of adverse effects on cardiovascular disease (CVD) outcomes [e.g., U.S. Environmental Protection Agency (EPA) 2009]. Although several mechanisms such as oxidative stress and inflammation have been suggested (Brook et al. 2010; Mills et al. 2009), it is not clear if specific chemical constituents of PM play distinct roles in any of these mechanisms. If PM toxicity could be determined based on specific chemical constituents or source types that emit such constituents, the regulation of PM may be implemented more effectively. Also, if a given adverse health outcome is associated with specific PM component(s) but not with others, then a specific mechanism may be postulated for further consideration by toxicological studies.

Recent multicity time-series studies of PM have generated important information regarding the possible role of sources but have also raised some issues that require further investigation. For example, the most comprehensive U.S.-based multicity study (Peng et al. 2005) of all-cause mortality (of which nearly half are from cardiovascular causes) similarly found the largest PM10 (aerodynamic diameter ≤ 10 µm) risk estimates in the northeastern cities but during the summer season. Thus, although both the hospitalization and mortality multicity studies found the strongest associations in northeastern cities, their seasonal patterns of associations are not consistent.

Several studies have examined the annual or seasonal average levels of PM2.5 chemical components as potential effect modifiers in a second-stage regression in order to try to explain city-to-city variation in short-term PM risk estimates from the first-stage time-series analysis in individual cities. Lippmann et al. (2006) reported that some of the city-to-city variation in the PM10–mortality risk estimates from the National Morbidity, Mortality, and Air Pollution Study could be explained by the variation in nickel (Ni) and vanadium (V) contents in PM2.5 across cities. However, Dominici et al. (2007) pointed out, in their analysis, that such a finding could be highly influenced by New York City (NYC) data (NYC has a large population and high Ni levels). A recent analysis by Bell et al. (2009) reported that the city-to-city variations in PM2.5 risk for both cardiovascular and respiratory hospitalizations among elderly persons were significantly modified by Ni, V, and elemental carbon (EC), suggesting that PM2.5 effects were stronger in locations with higher residual oil-burning-related and traffic-related pollution, highlighting the importance of local combustion sources, Bell et al. (2009) also found that sulfate (SO4) was not a significant predictor of city-to-city variation in PM2.5 risks. In an analysis of 25 U.S. cities, which did not include NYC, Franklin et al. (2009) found that the PM2.5–mortality risk estimates were significantly modified by aluminum, arsenic, silicon (Si), SO4, and Ni. In their analysis of 27 U.S. cities, Zanobetti et al. (2009) observed that the association between PM2.5 and CVD hospitalizations was significantly modified when the PM was high in bromine (Br), chromium (Cr), Ni, and sodium ion (Na+). Overall, these studies show mixed results, and because PM2.5 chemical constituents were treated as effect modifiers of PM mass concentration effects on mortality or hospitalizations, they do not necessarily suggest that these individual chemical constituents are associated with the health outcomes on a day-to-day basis.

Few studies to date have examined daily PM chemical constituents in relation to health outcomes. In an analysis of Phoenix, Arizona, Mar et al. (2000) examined several key PM2.5 chemical components in addition to PM2.5 and gaseous pollutants. They found that EC was significantly associated with CVD mortality, but they also found similar associations with nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and PM2.5.
Ostro et al. (2007) analyzed data from nine California counties and reported an association between cardiovascular mortality and several chemical constituents, including EC, organic carbon (OC), nitrate (NO₃⁻), iron, and potassium, at various lags. Peng et al. (2009) examined associations between elderly hospital admissions and seven PM₂.₅ chemical constituents that contributed substantial mass fractions to overall mass (EC, OC, SOₓ, NOₓ, Na⁺, Si, and ammonium ion) in 119 U.S. cities and found that EC was significantly associated with CVD hospitalizations. These studies either did not examine the PM₂.₅ chemical species whose mass contributions were low (e.g., Ni, V) or conduct analyses in the cities where the levels of these species were low.

The mortality and hospitalization studies noted above have examined the same or similar range of categories based on the International Classification of Diseases, 9th Revision (ICD-9; World Health Organization (WHO) 1977) and 10th Revision (ICD-10; WHO 2007) for CVD, but none of them examined both CVD mortality and hospitalizations in the same analysis or compared how these two CVD outcomes relate to each other or to other covariates in the regression models. Investigation of the apparent discrepancy in seasonal and regional pattern of associations between PM and these outcomes would benefit from a direct comparison of these CVD outcomes and characteristics of their relationships to PM₂.₅ chemical constituents and other pollutants.

The objective of our analysis was to examine the role of key PM₂.₅ chemical constituents on both CVD hospitalizations and mortality in NYC. NYC has one of the nation’s highest levels of Ni, presumably from the combustion of relatively “dirty” residual oils in large buildings for space heating (Peltier et al. 2009), as well as from the ships in the Port of New York ship terminals in Newark and Elizabeth, New Jersey, that burn so-called “bunker fuels,” which are heavy residual oils. NYC also has the nation’s highest density of traffic. In addition, during warm seasons, a major fraction (50–80%) of PM₂.₅ in NYC is transported secondary SOₓ and associated chemical constituents (Lall and Thurston 2006). NYC’s very large population also provided sufficient statistical power to examine the association between the CVD outcomes and PM₂.₅ chemical speciation data that were collected every third day.

Table 1. Distribution of daily CVD mortality and hospitalization, weather, and air pollution variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>All year</th>
<th>Warm season</th>
<th>Cold season</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean ± SD</td>
<td>IQR</td>
<td>Mean ± SD</td>
</tr>
<tr>
<td><strong>Mortality (counts/day)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>3.5 ± 2.0</td>
<td>3.0</td>
<td>3.3 ± 1.9</td>
</tr>
<tr>
<td>Myocardial infarction</td>
<td>10.7 ± 3.8</td>
<td>5.0</td>
<td>9.9 ± 3.7</td>
</tr>
<tr>
<td>Ischemic heart disease</td>
<td>42.1 ± 8.2</td>
<td>11.0</td>
<td>39.4 ± 7.1</td>
</tr>
<tr>
<td>Heart failure</td>
<td>1.7 ± 1.4</td>
<td>2.0</td>
<td>1.7 ± 1.3</td>
</tr>
<tr>
<td>Stroke</td>
<td>1.8 ± 1.4</td>
<td>2.0</td>
<td>1.8 ± 1.4</td>
</tr>
<tr>
<td>CVD (sum of above)</td>
<td>58.8 ± 10.4</td>
<td>13.0</td>
<td>56.0 ± 8.7</td>
</tr>
<tr>
<td><strong>Hospitalizations (counts/day)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>5.5 ± 2.9</td>
<td>4.0</td>
<td>5.3 ± 2.9</td>
</tr>
<tr>
<td>Myocardial infarction</td>
<td>41.0 ± 9.0</td>
<td>12.0</td>
<td>39.7 ± 7.3</td>
</tr>
<tr>
<td>Ischemic heart disease</td>
<td>64.6 ± 25.2</td>
<td>44.0</td>
<td>64.9 ± 24.9</td>
</tr>
<tr>
<td>Dysrhythmia</td>
<td>41.0 ± 11.1</td>
<td>17.0</td>
<td>41.6 ± 12.1</td>
</tr>
<tr>
<td>Heart failure</td>
<td>74.8 ± 16.5</td>
<td>24.0</td>
<td>73.2 ± 16.2</td>
</tr>
<tr>
<td>Stroke</td>
<td>54.4 ± 9.7</td>
<td>13.0</td>
<td>54.8 ± 9.4</td>
</tr>
<tr>
<td>CVD (sum of above)</td>
<td>261.3 ± 50.8</td>
<td>106.0</td>
<td>276.6 ± 50.1</td>
</tr>
<tr>
<td><strong>Weather (°C)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dew point</td>
<td>5.81 ± 10.18</td>
<td>16.57</td>
<td>12.78 ± 6.8</td>
</tr>
<tr>
<td>Apparent temperature</td>
<td>12.6 ± 10.96</td>
<td>19.32</td>
<td>20.73 ± 8.04</td>
</tr>
<tr>
<td><strong>PM₂.₅ components (µg/m³)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EC</td>
<td>1.13 ± 0.56</td>
<td>0.62</td>
<td>1.03 ± 0.51</td>
</tr>
<tr>
<td>OC</td>
<td>4.3 ± 2.28</td>
<td>2.38</td>
<td>4.51 ± 2.62</td>
</tr>
<tr>
<td>SOₓ</td>
<td>4.14 ± 3.29</td>
<td>3.19</td>
<td>4.81 ± 4.01</td>
</tr>
<tr>
<td>NOₓ</td>
<td>2.12 ± 1.98</td>
<td>2.19</td>
<td>1.52 ± 1.32</td>
</tr>
<tr>
<td>Na⁺</td>
<td>0.14 ± 0.11</td>
<td>0.11</td>
<td>0.14 ± 0.11</td>
</tr>
<tr>
<td>V</td>
<td>0.0017 ± 0.0013</td>
<td>0.0014</td>
<td>0.0111 ± 0.0097</td>
</tr>
<tr>
<td>Zn</td>
<td>0.0006 ± 0.0005</td>
<td>0.0006</td>
<td>0.0054 ± 0.0035</td>
</tr>
<tr>
<td>Si</td>
<td>0.0769 ± 0.0712</td>
<td>0.0743</td>
<td>0.0868 ± 0.0898</td>
</tr>
<tr>
<td>Se</td>
<td>0.0013 ± 0.0012</td>
<td>0.0013</td>
<td>0.0009 ± 0.0009</td>
</tr>
<tr>
<td>Br</td>
<td>0.0306 ± 0.0025</td>
<td>0.0051</td>
<td>0.0009 ± 0.00020</td>
</tr>
<tr>
<td><strong>Gaseous pollutants</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NOₓ (ppb)</td>
<td>28.7 ± 8.8</td>
<td>11.5</td>
<td>27.5 ± 8.6</td>
</tr>
<tr>
<td>SOₓ (ppb)</td>
<td>7.4 ± 6.1</td>
<td>6.6</td>
<td>3.9 ± 2.6</td>
</tr>
<tr>
<td>CO (ppm)</td>
<td>1.0 ± 0.43</td>
<td>0.5</td>
<td>0.94 ± 0.35</td>
</tr>
</tbody>
</table>

*For all gaseous pollutants, the range of category included the mean plus or minus twice the standard deviation.*
smoothers to smooth periodograms, applying several spans of smoothing over frequency, as suggested by Venables and Ripley (2002).

To characterize bivariate temporal relationships among weather, air pollution, and health outcome variables, we computed the cross-correlation function (CCF; correlation with lags) for key variables considered. These cross-correlations can indicate the sequence of temporal fluctuations (i.e., which variable leads the other in time). The correlation between two time series can be strongly influenced by shared trends, seasonal cycles, and day-of-week patterns that may be confounding. Therefore, in order to remove the influence of these temporal patterns and to focus on the short-term relationships between the variables, each time series was first prefiltered in a generalized linear model using a natural cubic spline smoothing function with 8 degrees of freedom per year and a day-of-week variable. A CCF was then computed using pairwise complete observations between the lagged residual time series. We chose 8 degrees of freedom per year to be consistent with the extent of adjustment for temporal trends in recent multicity time-series analyses (e.g., Bell et al. 2009; Samoli et al. 2008). Because relationships among these variables can change across seasons, the CCF was computed in a series of 12 three-month blocks centered on each month of the year and pooled for the entire 7-year study period.

Regression models. We estimated percent excess risk (%ER) for air pollutants using a Poisson time-series model, adjusting for temporal trends and seasonal cycles, immediate and delayed temperature effects, and day of the week. The extent of lagged days considered for air pollution and weather variables were based mainly on recent time-series studies and the exploratory analysis of these data described above. We used natural cubic splines of days to adjust for potentially confounding temporal trends and seasonal cycles using 8 degrees of freedom per year in our base model. To adjust for immediate and delayed non-linear temperature effects, our base model also included natural cubic splines of the same-day and the average of past 1- through 3-day lagged temperature with 3 degrees of freedom over the range for each term. Temperature and dew point were highly correlated (r = 0.93) in this data set, so we did not include them simultaneously. We did, however, compute apparent temperature from temperature and dew point (Steadman 1979) and included it in a separate alternative model for sensitivity analysis. Risks were estimated at lags 0 through 3 days for interquartile-range (IQR) increases of pollutants for all-year data (Table 1) and for all-year, warm (April through September), and cold (October through March) seasons. All the statistical analyses were conducted using the R statistical software package (version 2.10.1; R Development Core Team 2009).

Results
CVD mortality and hospitalization time series exhibited markedly different characteristics. Figure 1 shows time series and corresponding

![Figure 1](image-url)
power spectra of these time series. CVD mortality showed a strong seasonal pattern, with broad winter peaks that vary from year to year, apparently reflecting influenza epidemics. A day-of-week pattern was not apparent in the CVD mortality power spectra, which showed a major variance contribution in the frequency range corresponding to seasonal cycles. In contrast, CVD hospitalizations showed substantial variance contribution from day-of-week cycle frequencies (0.14/day or 7-day cycle, and its harmonics), which is stronger than that from seasonal cycles. CVD hospitalizations were lower on Saturday and Sunday, with hospitalizations about 60% higher on Monday than on Sunday. Likewise, the power spectra for specific CVD hospitalizations all showed strong day-of-week peaks that were stronger than those for seasonal cycles (data not shown).

Table 1 shows distributional characteristics of CVD outcome, weather, and air pollution variables. The largest fraction of CVD mortality was from ischemic heart disease, followed by myocardial infarction. CVD hospitalizations were more evenly divided by the specific categories. Ni, V, Zn, and SO₂, all likely associated with residual oil burning, showed substantially higher levels in cold seasons than in warm seasons. Correlations among air pollutants by season are shown in Supplemental Material, Table 1 (doi:10.1289/ehp.1002667).

The following results from CCF and regression analysis necessarily involve multiple testing because of multiple lags, pollutants, and outcomes examined. Therefore, to guard against overinterpretation of chance findings, we focus not on the statistical significance of individual results but instead on identifying consistent patterns and contrasts of results across the lags, pollutants, and outcomes.

In the CCF analysis of key variables, after removing seasonal cycles and day-of-week patterns, temperature showed different patterns of associations with CVD mortality versus CVD hospitalizations, respectively (Figure 2A,B). With CVD mortality, temperature showed positive associations in summer and lagged negative associations in winter, consistent with fairly well-known mortality impacts of temperature reported in the past literature (e.g., Curriero et al. 2002). In contrast, CVD hospitalizations showed immediate and positive associations with temperature in the cold season, clearly not heat events, and biologically implausible. There was also a suggestion of lagged negative associations between temperature and CVD hospitalizations in the warm season and the beginning of the cold season.

We repeated the analysis using apparent temperature rather than temperature (data not shown), but the pattern and magnitude of associations were essentially unchanged.

The CCF relationships between PM₂.₅ and CVD mortality and hospitalizations also showed contrasting patterns (Figure 2C,D). PM₂.₅ was positively associated with CVD mortality in the warm season with lags 0 and 1 day, whereas it was positively associated with CVD hospitalizations in the cold season, most consistently at lag 0 day. The CCF for chemical components of PM₂.₅ versus CVD outcomes showed less distinct patterns (data not shown), likely in part due to the smaller sample size (only every third day). The CCF relationship between temperature and PM₂.₅ chemical components showed generally positive associations on the same day throughout the year and delayed negative associations in cold seasons, but the relationship between temperature and Ni showed negative associations with longer lags and no positive associations in the cold season [Supplemental Material, Figure 1d (doi:10.1289/ehp.1002667)].

We found no correlation between CVD hospitalizations and CVD mortality, except for as weak negative correlation in the cold season (Figure 2E). This is consistent with the contrasting relationships between these CVD outcomes and temperature or PM₂.₅. The CCFs between specific CVD hospitalizations

![Figure 2](https://example.com/figure2.png)

Figure 2. Cross-correlation function (CCF) between X = temperature, Y = CVD mortality (A); X = temperature, Y = CVD hospitalizations (B); X = PM₂.₅, Y = CVD mortality (C); X = PM₂.₅, Y = CVD hospitalizations (D); and X = CVD hospitalizations, Y = CVD mortality (E): a correlation below the centerline (lag 0) indicates that X leads Y, and a correlation above the centerline indicates that Y leads X. Black bars are positive correlations, and white bars are negative correlations (correlations whose absolute values are < 0.1 are not shown). The lengths of reference correlations (0.25 and 0.50) are also shown. CCFs were computed after removing seasonal trends and day-of-week pattern (see "Results"). Abbreviations: X, predictor; Y, outcome.
and corresponding CVD mortality (e.g., CCF between heart failure hospitalizations and heart failure mortality) likewise did not show associations (data not shown).

Figure 3 shows air pollution–CVD mortality regression results (see Table 1 for IQRs used to compute %ER). PM$_{2.5}$ was associated with CVD mortality in the warm season at lag 0 (%ER = 2.0%; 95% confidence interval (CI), 0.7–3.3; per 10 µg/m$^3$) and lag 1 day (1.9%; 95% CI, 0.8–3.1) and in the cold season at lag 1 day (1.0%; 95% CI, -0.1 to 2.2). OC and SO$_4$, both of which are associated with a major mass fraction of PM$_{2.5}$ during the warm season (i.e., secondary aerosols), also showed significant associations with CVD mortality in the warm season at lags 0 and 1 days, with estimated %ERs similar to those for PM$_{2.5}$ per IQR increase. Se, primarily associated with transported coal emissions in the eastern United States, and also associated with transported SO$_4$, showed a strong association with CVD mortality at lag 1 day. EC was significantly associated with CVD mortality at lag 1 day in the warm season and was nearly significant in the cold season also at lag day 1. Br (perhaps associated with traffic) was strongly associated with CVD mortality at lag 0 in the warm season. Ni, V, and Zn (the elements most associated with residual oil burning in NYC) showed a similar pattern of associations with CVD mortality, with stronger associations in the cold season at lag 3 days. Na$^+$ (considered to be a signature element for sea salt) also showed nearly a significant positive association at lag 0 day in both warm and cold seasons. Among the gaseous pollutants, NO$_2$ showed lag 1-day positive associations with CVD mortality in both warm and cold seasons. There are peculiar negative (significant or nearly significant) associations for a number of pollutants at lag 0 day in the cold season (PM$_{2.5}$, OC, Ni, Zn, Si, Se, NO$_3$, NO$_2$, SO$_4$, and CO). These pollutants were not negatively correlated with CVD mortality in the CCF analysis (data not shown), and the negative associations may be induced by the adjustment for temperature. Not surprisingly, among the specific CVD mortality categories, mortality for ischemic heart disease showed a similar pattern of association as that for total CVD mortality (data not shown). The relationships between air pollutants and hospitalizations showed a pattern of association different than that for CVD mortality (Figure 4). The associations between air pollution and CVD hospitalizations, in contrast to CVD mortality, were generally stronger in the cold season than in the warm season. The exceptions were EC, NO$_2$, SO$_2$, and CO, which showed similar magnitude and lag structure of associations in both seasons. PM$_{2.5}$ exhibited the strongest association at lag 0 day in the cold season (%ER = 1.1; 95% CI, 0.2–2.0), and most of the PM$_{2.5}$ chemical components that showed significant or near significant associations (OC, SO$_4$, Ni, Zn, Si, Se, and Br) with CVD hospitalizations showed the strongest associations at lag 0 day in the cold season. Of the specific CVD hospitalizations, those for hypertensive disease, ischemic heart disease, dysrhythmias, and stroke showed patterns of associations similar to that for total CVD hospitalizations (data not shown). Seasonal patterns of associations, lags, source types, and %ER are summarized for CVD mortality and hospitalizations in Supplemental Material, Table 2 (doi:10.1289/ehp.1002667).

These results were not sensitive to the alternative model in which we used apparent temperature rather than temperature to adjust for weather effects. Supplemental Material, Figure 2 (doi:10.1289/ehp.1002667), shows comparisons of risk estimates for CVD mortality and hospitalizations using temperature and apparent temperature for the warm and cold seasons.

Figure 3. %ER for CVD mortality per IQR increase in air pollutant, adjusted for temporal trend, day-of-week, same-day, and delayed temperature effects.

Figure 4. %ER for CVD hospitalizations per IQR increase in air pollutant, adjusted for temporal trend, day-of-week, same-day, and delayed temperature effects.
seasons. There appears to be no systematic difference in the risk estimates obtained from these models.

**Discussion**

We found that adult CVD mortality and emergency CVD hospitalizations time series, when constructed with consistent ICD categories, were not correlated over time. The CVD mortality series showed a strong influence of seasonal cycles and influenza, whereas CVD hospitalizations were strongly influenced by a day-of-week pattern, with little seasonal pattern. Their relationships with temperature, as examined in our seasonal CCF analysis, were also different. The strong influence of the day-of-week pattern seen in CVD hospitalizations (lower counts on weekends) may imply that they are more strongly influenced by behavioral modification factors than by CVD mortality (e.g., being able to delay seeking treatment over the weekend). Also, it is possible that coding practice and conditions under which a “primary cause” is assigned to these outcomes may be different. For example, if a person with a chronic ischemic heart condition dies with an additional complication of influenza-related pneumonia, the primary cause of death may still be recorded as a heart-disease-related cause, whereas when a person with an acute cardiovascular condition is admitted to a hospital through the emergency department, the primary cause may be less ambiguous. If such differences contribute to the apparent lack of correlation between these two CVD outcomes, then the subgroups at risk for PM effects within these CVD outcomes need not share the same risk characteristics or even the same mechanism(s) of PM effects. However, in this analysis, we did not specifically examine whether some of those who were hospitalized died later, or whether a subgroup’s hospitalizations were associated with air pollution. If the fraction of each subgroup is relatively small in the overall CVD hospitalizations, then we may not see significant lagged correlation between CVD hospitalizations and mortality, whether or not they are associated with air pollution in the same causal pathway.

CVD mortality’s immediate association with high temperature in the warm season and lagged association with cold temperature in the cold season found in our analysis are consistent with expectation and the past literature. However, the lack of heat effects on CVD hospitalizations in warm seasons and the presence of positive associations in cold seasons (i.e., the warmer the temperature, the more CVD hospitalizations) found in this study is somewhat surprising, although it is in part consistent with “a protective effect of cold temperature” (i.e., the lack of the left side of the U-shape in the temperature-outcome relationship) that was reported by Schwartz et al. (2004) who analyzed temperature and elderly CVD hospitalizations in 12 U.S. cities. Also, in another analysis of CVD hospitalizations in NYC, whereas the overall CVD hospitalizations were positively associated with high temperature, the hospitalizations for CVD, heart failure, and hypertension showed negative risk estimates (Lin et al. 2009). Thus, there may be heterogeneity in temperature effects within subcategories of CVD hospitalizations.

In these analyses, CVD mortality was more strongly associated with PM$_{2.5}$ in the warm season than in the cold season, whereas CVD hospitalization was more strongly associated with PM$_{2.5}$ in the cold season than in the warm season. These findings are consistent with the results of the analysis in the U.S. Northeast of (all-cause) mortality and PM$_{10}$ (Peng et al. 2005) and the analysis of CVD hospitalizations and PM$_{2.5}$ (Bell et al. 2008). The lag structures of PM$_{2.5}$ associations for CVD mortality (lags 0 and 1 day) and CVD hospitalizations (lag 0 day) are consistent with those found in past multicity studies for mortality (Peng et al. 2005) and CVD hospitalizations (Bell et al. 2008; Dominici et al. 2006; Peng et al. 2009).

The patterns of lagged associations between individual PM$_{2.5}$ chemical components and CVD mortality were not always consistent with those for PM$_{2.5}$ mass concentrations. It is not surprising that SO$_2$ and OC were associated with CVD mortality on the same lag days (0 and 1) as PM$_{2.5}$ because both SO$_2$ and OC contribute major mass fractions to PM$_{2.5}$. Si, a marker of soil whose associated species together contribute significant amounts of particulate mass, also showed the same lag structure of associations. However, other PM chemical components with smaller mass contributions showed different lagged associations with CVD mortality compared with PM$_{2.5}$. Ni, V, and Zn (i.e., the species associated with residual oil burning in NYC) all showed delayed associations (largest estimates at lag 3 days) with CVD mortality. However, this may reflect the relationship between temperature and these species in the cold season [see Supplemental Material, Figure 1 (doi:10.1289/ehp.1002667)], which was negative with long lags and had no positive associations on the same day. Therefore, caution is required in interpreting these lagged associations between PM components and health outcomes, because they may have varying relationships with other covariates in the regression model. Also, the 3-day lagged association between Ni and CVD mortality is not necessarily consistent with Ni’s effect modification of 1-day lagged PM$_{10}$-mortality associations suggested in Lippmann et al.’s (2006) result.

We observed the associations between CVD hospitalizations with air pollutants primarily in the cold season, except for EC, Na$^+$, NO$_2$, SO$_2$, and CO, which were associated in both seasons. Because most of the PM$_{2.5}$ chemical components and gaseous pollutants examined similarly yielded significant or nearly significant associations at lag 0 day, it is difficult to draw inferences on which chemical components or sources may be more important for the PM$_{2.5}$ association with CVD hospitalizations in this data set. These results are, in part, consistent with the significant effect modifiers (EC and Ni) of PM$_{2.5}$ effects on elderly CVD hospitalizations reported in the Bell et al. (2009) analysis or those (Br and Ni) reported in the Zanobetti et al. (2009) analysis but show a broader spectrum of PM$_{2.5}$ source components contributing to effects.

Given the lack of correlation between CVD hospitalizations and CVD mortality over time, we did not expect “coherence” in specific PM$_{2.5}$ chemical components’ association with these two CVD outcomes. Of the pollutants examined, EC and NO$_2$ showed the most consistent associations with these CVD outcomes, in that these pollutants showed the same extent of associations in both warm and cold seasons with the same lags (lag 1 day for CVD mortality and lag 0 day for CVD hospitalizations). Both EC and NO$_2$ are often considered to be “signature” tracers for traffic sources. However, EC may be emitted from other fuel combustions, including oil boiler emissions (Schauer 2003). Likewise, NO$_2$ is also emitted from a variety of combustion sources. In fact, in the New York City Community Air Survey conducted during the winter of 2008 and 2009, which measured PM$_{2.5}$, its chemical components, and gaseous pollutants at 150 locations in NYC, land-use regression analysis found that both traffic and building density (i.e., proxy for building space heating) were significant predictors of EC and NO$_2$ in this city (NYCDOHMH 2009). This does not directly imply that these pollutants per se are responsible for the health effects, but they may be important indicators of sources relevant to the PM$_{2.5}$ effects on CVD outcomes.

The relative significance of the associations of the PM components with CVD outcomes could have been influenced by their corresponding exposure misclassification errors that include the error associated with the locations of monitors relative to the population. An investigation related to this issue involving the same three speciation monitors (Ito et al. 2004) found that the PM$_{2.5}$ chemical species associated with regional secondary aerosols (e.g., SO$_2$ and NO$_2$) tend to have higher monitor-to-monitor temporal correlations than do the species associated with more local combustion sources (e.g., EC and Ni). Thus, the interpretation of our study findings is limited by the uncertainty regarding the influence of relative exposure error across the species on the observed associations.
Conclusion

We found that CVD hospitalizations and CVD mortality time series are not correlated, but they are each independently associated with a number of PM$_{2.5}$ chemical components, including both regional secondary aerosols and local combustion sources. EC and NO$_2$ showed the most consistent associations with these CVD outcomes throughout the year, but the PM components associated with the regional transported aerosols from coal combustion (Se and SO$_4$) exhibited the season-specific association pattern most similar to that of PM$_{2.5}$ mass. We conclude that local combustion sources, including traffic and residual oil burning, may be important sources affecting CVD adverse effects in NYC.

References


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