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Asthma exacerbation is associated with particulate matter source factors in children in New York City

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Abstract Exposure to fine particulate matter ($PM_{2.5}$) is linked with asthma exacerbation; however, the role played by specific PM sources is not well understood. Our objective was to investigate the associations between daily cough and wheeze symptoms in a panel of asthmatic children and PM source factors determined by receptor modeling using positive matrix factorization (PMF). We studied 36 children with moderate-to-severe asthma in New York City over both a warm and a cold season. Exposure to ambient air pollutants, including $PM_{2.5}$ elements and elemental and organic carbon fractions, was characterized. The mean ambient $PM_{2.5}$ concentration for the study periods was 12.0± 6.7 μg/m^3. Six factors were resolved using PMF, including oil, road dust, ships, regional, salt, and traffic. When adjusted for ozone, cough and wheeze symptoms were most strongly associated with the regional and salt factors. Results using tracer elements (as determined from PMF analyses) showed some inconsistency, with two tracers for road dust (K and Si) showing associations in opposite directions to each other. Positive associations were also observed for S, which is a tracer of regional PM. Significant negative associations were observed for the oil factor and one of its tracers (Zn). Mostly nonsignificant associations were found for carbon fractions, with the exception of pyrolized carbon and two elemental carbon fractions. Our results indicate that asthma symptoms are associated with regional and salt factors. In this study, the regional factor was comprised of sulfate as well as carbon-containing PM, the latter which is likely derived from both anthropogenic and biogenic sources.

Keywords Air pollution · Particulate matter · Asthma · Pulmonary function · Source apportionment

Abbreviations

EC	Elemental carbon
OC	Organic carbon
$PM_{2.5}$	Particulate matter with aerodynamic diameter <2.5 μm
PMF	Positive matrix factorization

Introduction

A number of epidemiological studies have reported associations between ambient fine particulate matter ($PM_{2.5}$) and asthma exacerbation (e.g., Dales et al. 2009; Silverman and Ito 2010). However, in other studies, no association between

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$PM_{2.5}$ and indicators of asthma was found; rather, individual components of ambient PM were reported to be so associated (Delfino et al. 2008; Patel et al. 2010). This suggests that PM composition plays an important role in the induction of adverse health outcomes and may even drive health responses. The concept of differential toxicity has been the topic of multiple reviews (e.g., Lippmann and Chen 2009; Kelly and Fussell 2012; Rohr and Wyzga 2012); from a public health policy perspective, determining which component(s) are most associated with health effects is of paramount importance.

Source apportionment, or receptor modeling, has been used to provide insight into the role played by various PM components and sources in different asthma-related endpoints. Andersen et al. (2007) examined hospital admissions for asthma in children aged 5–18 in Copenhagen, Denmark. These investigators conducted source apportionment of PM_{10} particles and identified six factors: biomass, secondary, oil, crustal, sea salt, and vehicle. Although none of the factors was statistically significantly associated with asthma admissions, the vehicle factor was most strongly associated. Halonen et al. (2009) examined a number of population health endpoints in Helsinki, Finland, including hospital admissions for asthma/chronic obstructive pulmonary disease, and related them to four source factors (traffic, long-range transport, soil/road dust, and coal/oil combustion). Results indicated that an increase in hospital admissions was positively and significantly associated with traffic and long-range transport source factors.

Several investigators have conducted panel studies. Gent et al. (2009) studied 149 children aged 4–12 in New Haven, USA, and examined associations between daily exposure to fine particle components and sources and symptoms and medication use in children with asthma. More than half of $PM_{2.5}$ was attributed to traffic-related sources (42 % motor vehicles and 12 % road dust). Increased likelihood of symptoms and inhaler use was largest for 3-day averaged exposures to traffic-related sources or their elemental constituents. None of the other sources identified (sulfur, biomass burning, oil, and sea salt) nor $PM_{2.5}$ alone was associated with increased risk. Penttinen et al. (2006), in a study of peak expiratory flow (PEF) and respiratory symptoms in 57 adult asthmatics in Helsinki, found that $PM_{2.5}$ attributable to local combustion, as characterized by high loadings of nitrogen oxides, $PM_{2.5}$ absorption coefficients (analogous to black smoke measurements), and ultrafine and accumulation mode particle numbers, was consistently negatively associated with all PEF measurements. $PM_{2.5}$ attributed to long-range transport was positively, and soil-derived $PM_{2.5}$ negatively, associated with PEF. No associations were observed between source-specific PM and respiratory symptoms or between individual elements and any endpoints.

The Children's Air Pollution Asthma Study involved studying a panel of 36 asthmatic children over two seasons (roughly winter and summer, but with some fall and spring days included). Both ambient (central site) and indoor residential air quality monitoring was conducted, and pulmonary function, albuterol use, and asthma symptoms were recorded on a daily basis. Analyses linking individual ambient pollutant exposures with asthma exacerbation will be reported in a separate publication. We also assessed exposures to particles of ambient and indoor origin and associated them with asthma symptoms (Habre et al. 2013). In the present analysis, we apply a commonly used source apportionment method to the ambient air quality dataset and explore associations between source factors and asthma in this group of high risk children. A unique feature of this work was the collection of thermally resolved elemental carbon (EC) and organic carbon (OC) fraction data; these were not included in the source apportionment but were considered post hoc in regression and health outcome analyses.

Methods

Study design and subject recruitment

The Children's Air Pollution Asthma Study included a panel of 36 asthmatic children living in East Harlem and South Bronx, NY, USA. The panel was studied over four different time periods: Winter 2008 (February–May 2008), Summer 2008 (June–September 2008), Winter 2009 (November 2008–April 2009), and Summer 2009 (June–October 2009). Our original intent was to study the participants in clearly defined winter and summer seasons; however, the study periods did run into fall and spring. For the purposes of this paper, we will refer to the study periods as "cold" and "warm." East Harlem and South Bronx were selected because of the elevated asthma prevalence in these areas compared to other parts of New York City (NYC Department of Health 2008). Each participant was studied over two consecutive 7-day periods during each of a cold and warm season, for a total of 28 sampling days per child. We monitored daily ambient air pollutant exposures and cough and wheeze symptoms simultaneously over the two study periods.

Participants were recruited from the Mount Sinai Hospital pediatric pulmonary clinic, asthma clinic, and emergency room. Eligibility criteria included (1) being symptomatic, (2) aged 6–14 years old, and (3) with doctor-diagnosed, persistent, moderate to severe asthma, defined by at least one of the following: daily use of controller medication for at least 3 months over the last year, use of a β-agonist at least four times per month in any one of the last 3 months, or nocturnal awakenings two times a month, once in the last 3 months. In addition, the child must sleep at the primary residence at least five times a week. Exclusion criteria included (1) active disease other than asthma requiring daily medications, (2) family

was planning to move from their current home within the next 6 months, and (3) family had members who smoked in the home. Parents/guardians of eligible children who were willing to participate in the study read and signed a Mount Sinai IRB approved consent form (IRB project 05-0679) and a HIPAA form.

Subject characteristics are shown in Table 1. More detailed information on the baseline questionnaire administered, which was based on an NIH questionnaire previously validated for the Inner City Asthma Study (Kattan et al. 2006), skin prick allergy testing, baseline home evaluation, and collection of dust samples for allergens, endotoxin, and glucans, will be reported in a subsequent publication.

Exposure assessment

An ambient monitoring station was operated on the roof of the City College of New York (CCNY) administration building in Northern Manhattan to collect outdoor pollutant data. Modified versions of Harvard Impactors with ChemComb inlets (Demokritou et al. 2001) were used to collect daily $PM_{2.5}$ samples on Teflon and prefired quartz filters. A new 24-h sample was started each day at 9:00AM local time using a Chrontrol (model XT-W8) sequential timer. $PM_{2.5}$ mass concentration was determined gravimetrically from Teflon filters. Elemental composition of $PM_{2.5}$ was determined by X-ray fluorescence analysis for 51 elements, along with their uncertainties. Prefired quartz filters were analyzed using the IMPROVE thermal optical reflectance protocol (TOR/IMPROVE) to determine the concentrations and uncertainties of thermally resolved carbon fractions (EC1, EC2, EC3, OC1, OC2, OC3, OC4, and OP) as well as total EC and OC. EC1 from the thermal/optical reflectance (TOR) analysis was corrected by subtracting the pyrolytic carbon (OP) fraction (Sahu et al. 2011). Daily averages were calculated for ozone (O_3) concentration from hourly data obtained from the New York State Department of Environmental Conservation (NYSDEC) CCNY site. Ambient average daily temperature was obtained from the National Climatic Data Center's New York Central Park Tower meteorology station. Relative humidity was obtained from the NYSDEC New York Botanical Gardens site.

Standard quality assurance and quality control procedures were carried out. Lab and field blank corrections were conducted, and negative values or concentrations below the limit of detection were retained to preserve data distribution.

Table 1 Cohort characteristics and symptom scores

	N	Mean (SD)		Median (min, max)
Child's age	36	9.8 (2.9)		9.4 (6.1,14.8)
Child's race/ethnicity				
Hispanic	36	23 (65 %)		
Black		13 (35 %)		
Child's gender				
Male	36	24 (65 %)		
Female		12 (35 %)		
Distribution of symptom scores (*N*=832 subject-days)				
Cough score	0	1	2	3
N (%)	560 (67 %)	177 (21 %)	61 (7 %)	34 (4 %)
Wheeze score	0	1	2	3
N (%)	690 (83 %)	90 (11 %)	39 (5 %)	13 (2 %)

Health outcome assessment

Each participant completed a daily diary during the two study periods, which included cough and wheeze symptoms, graded as 0–3 severity.

Data analysis

Descriptive statistics were calculated for participant demographics, asthma symptoms, and environmental variables.

Source apportionment analyses

The positive matrix factorization (PMF) model was used to apportion measured $PM_{2.5}$ concentrations into its major contributing factors or "sources" using EPA PMF v3.0 (Paatero and Tapper 1994; Paatero 1997; Norris et al. 2008).

The PMF model solves the following equation:

$$x_{ij} = \sum_{k=1}^{p} g_{ik} f_{kj} + e_{ij} \quad (1)$$

where x_{ij} is the concentration of species i in sample j, g_{ik} is the mass contribution of factor k to sample i, f_{kj} is the loading of species j on factor k, and e_{ij} is the residual for sample i and species j.

PMF solves Eq. (1) by minimizing the following object function:

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} \left[\frac{e_{ij}}{u_{ij}}\right]^2 \quad (2)$$

where u_{ij} is the uncertainty of species j in sample i.

Therefore, each observation is individually weighted by its uncertainty. Elements of the G and F matrix are restricted to being positive.

Days with complete data for elements, EC, OC, and $PM_{2.5}$ mass were included in the analysis, resulting in 371 observations. Outliers and days following 4th of July celebrations were excluded (total of 11 days: 6/14/2008, 6/28/2008, 7/4–7/5/2008, 1/26/2009, 2/8/2009, 7/2–7/6/2009). The final data set included 360 days.

"Strong" and "weak" species were included in the analysis, and "bad" species were excluded, based on the PMF-calculated signal/noise ratio (S/N) as follows: "strong" S/N≥2, "weak" 1≤S/N<2, and "bad" S/N<1. Setting species as "weak" increases their uncertainty by a factor of 3. The following 22 species were included in the PMF analysis as "strong", except where noted, in addition to $PM_{2.5}$ mass: EC, OC, sodium (Na), aluminum (Al), silicon (Si), sulfur (S), chlorine (Cl), potassium (K), calcium (Ca), titanium (Ti), vanadium (V), manganese (Mn), iron (Fe), nickel (Ni), copper (Cu), zinc (Zn), arsenic (As, "weak"), selenium (Se, "weak"), bromine (Br), strontium (Sr, "weak"), molybdenum (Mo, "weak"), and lead (Pb). Although Se had S/N=0.92, it was included in the analysis as a potential tracer of coal combustion and set to "weak". Sn had S/N=5.7 but was later excluded due to its very poor R^2 (2 %) and non-normal residuals.

$PM_{2.5}$ uncertainty was calculated as 5 % of its mass. $PM_{2.5}$ mass was designated as the total variable and set to "weak". An additional 10 % modeling uncertainty was added to account for sampling or modeling errors not captured in the sample specific uncertainties. Twenty-five model runs were performed and the convergent solution with the lowest Q_{robust} value was selected. Solutions with five, six, and seven factors were attempted, and a six-factor solution was selected based on the most physically interpretable results with the least factor smearing and most normal residuals.

Residuals were inspected for normality and solution stability, and variability in predicted profiles was evaluated by performing 100 bootstraps with a minimum correlation of 0.6 for mapping a base factor to a bootstrap factor. Factors were identified based on the temporal trends in their contributions and the loading of species in their profiles.

Including the thermally resolved carbon fractions in the PMF model resulted in nonconvergence. In order to estimate their loading profiles on the predicted sources, the carbon fraction concentrations were regressed on the estimated source contributions (model included an intercept and predicted contributions of all sources). However, since total EC and OC were included in the PMF model to resolve these sources, and because of the high uncertainty in the concentrations, regression results should be interpreted in a qualitative rather than quantitative manner. Negative loading profiles were reported as null or missing values.

Health effects analyses

Mixed proportional odds models for an ordinal categorical outcome were applied to assess cough and wheeze symptom scores in relation to daily source contributions and their lags. Let i index each subject-season combination. The primary model was as follows:

$$\text{logit}(\mathrm{P}[Y_{it} > j]) = \beta_{0j} + b_i + \beta_1 \textit{Source Contribution}_{it} + \delta W_{it} + \gamma U_i + \varepsilon_{it}, j = 2,3,4. \quad (3)$$

where Y_{it} is the cough or wheeze score of subject i on day t, and logit(.) is a cumulative logit link function used to relate the probability of more severe cough or wheeze compared with less severe symptoms for a change in source factor concentration. The model makes the proportional odds assumption, which states that the effect of each covariate in the model does not vary by the logit cutpoint j. The β_{0j} are fixed intercepts and b_i is a random intercept for each subject/season combination. This random effects structure was selected because of the high variability in asthma symptoms between subjects and between seasons; more severe symptoms are generally experienced in the winter. W_{it} is the vector of time-varying, fixed covariates for subject i on day t: ambient temperature (°C) and relative humidity (%). U_i is the vector of time-invariant, fixed covariates for subject/sampling season i: gender (male, female), race (Hispanic, black), and season (defined by month as fall, winter, spring, or summer).

Univariate models were first fit for source factor concentrations. In secondary analyses, ambient O_3 was added to these models to evaluate potential confounding. Odds ratios were calculated for a standard deviation increase in source factor mass contribution. Models were fit in SAS 9.2 using PROC GLIMMIX, and figures were generated in JMP Pro 10.0.2 (SAS Institute Inc., NC, USA). We investigated associations with same-day exposures [lag 0 (L_0)] as well as varying lags ranging from 1 day [lag 1 (L_1)] to 3 days [lag 3 (L_3)], as well as the mean of the lagged days [lag 0–3 (L03)]. We selected this lag structure based on previous similar work (Gent et al. 2009).

We also ran univariate models with source tracer elements to evaluate consistency with source apportionment results. Tracers were selected based on their enhanced loadings onto source factors (described below) and their high correlations with the source factor itself. Models were identical to those described above. In addition, we ran identical univariate models with EC and OC fractions.

Results

Exposure assessment

Ambient pollutant concentrations are provided in Table 2. The mean $PM_{2.5}$ mass concentration during the study period was

Table 2 Ambient pollutant concentrations (all ng/m^3 unless otherwise noted)

	N	Mean	SD
$PM_{2.5}$ (μg/m^3)	360	12.0	6.7
EC (μg/m^3)	360	1.3	0.7
OC (μg/m^3)	360	1.8	1.1
EC1	360	908.6	634.6
EC2	360	337.6	170.2
EC3	360	20.1	33.2
OC1	360	−82.3	235.1
OC2	360	630.5	553.3
OC3	360	465.2	296.0
OC4	360	373.5	209.1
OP	360	437.9	281.0
Al	360	25.4	14.9
Si	360	47.6	29.1
S	360	1,073.9	672.8
Cl	360	22.5	57.0
K	360	43.0	24.6
Ca	360	72.9	34.2
Ti	360	3.6	2.2
V	360	3.9	3.4
Mn	360	3.6	2.1
Fe	360	104.3	48.9
Ni	360	8.8	7.4
Cu	360	4.4	2.1
Zn	360	32.1	18.8
As	360	0.1	0.3
Se	360	0.2	0.4
Br	360	1.8	1.5
Sr	360	0.7	0.6
Mo	360	1.5	1.0
Na	360	184.9	153.8
Pb	360	3.1	1.8
Ozone (ppb)	351	19.9	10.6
Temperature (°C)	359	13.5	10.5
Relative humidity (%)	360	74.6	14.3

12.0±6.7 μg/m^3. Total carbon (OC+EC) constituted on average 26 % of $PM_{2.5}$ mass. Over half of the carbon was in the form of OC (58 %), with 42 % in the form of EC. Of the carbon fractions, EC1 and OC2 were present at the highest concentrations (909 and 630 ng/m^3, respectively). Ammonium sulfate, calculated from elemental S, was present at 4.4 μg/m^3, or 37 % of $PM_{2.5}$ mass. Of the trace elements measured, Na, Fe, and Ca were present at the highest concentrations.

Source apportionment

The PMF model fit was evaluated and found to be stable with no undue influence of outliers (Q_{robust}=8,709.8 and Q_{true}=9,114.4). No factors were unmapped in the bootstraps. Most species were well modeled except for As and Se with very poor R^2 values. The species Cl, K, V, Fe, Cu, As, and Se had non-normal residuals.

PMF resolved six factors; loadings are shown in Fig. 1, with numerical data provided in Supplemental Table S-1. The first was primarily loaded with Ni, Zn, and Pb, and we termed this a "combined oil/incineration" factor, with the Ni primarily from oil combustion and the Zn primarily from incineration. Other work in New York City has identified such a mixed factor (Ito et al. 2004; Qin et al. 2006). A factor we termed "road dust" was heavily loaded with trace elements associated with crustal material (Al, Si, Ca, Ti, Mn, and Fe), as well as organic carbon. A "regional pollution" factor was associated with high S, with some loading of OC as well. A "salt" factor was represented primarily by Na, Cl, and Br and is likely to include contributions of both sea salt and road salt; the latter is included due to the wintertime peaks in this factor's contribution to PM (Figure S-1, Supplemental Material). One factor was significantly loaded only with V, plus some EC and OC, which we suggest represents "ships," consistent with the findings of Peltier and Lippmann (2010) who have suggested that the Port of New York is the major source of V in New York City. Finally, a "traffic" factor was characterized by high EC and OC, Cu, and Pb. Correlations between source factors are presented in Supplemental Table S-2.

Tracers were selected based on their loadings onto specific source factors and their high correlations with the source factors themselves (Table 3). For road dust, we selected Al, Fe, K, and Si, with Pearson's correlation coefficients of 0.82, 0.61, 0.44, and 0.96, respectively. Tracers for the combined oil/incineration factor were Ni (Pearson's r=0.90) and Zn (0.85). For the regional factor, S (0.94) and pyrolized organic carbon (0.65) were selected. Vanadium was used as the tracer for the ships factor, with a Pearson's r of 0.95, and EC and OC were tracers for the traffic factor (0.68 and 0.45, respectively). Finally, for the salt factor, we selected Na, with a Pearson's r of 0.33. Chlorine was much more highly correlated with this factor (r=0.99); however, it is not a good tracer because it reacts with H_2SO_4 in the atmosphere or on the filter displacing Cl^- as HCl, which then escapes (Pio and Lopes 1998). This is supported by the low correlation between Na and Cl (r=0.30). A correlation matrix for all PM components (not only the tracers) is presented in Supplemental Table S-3.

Factor contributions to overall mass are provided in Table 4. The largest contributor to $PM_{2.5}$ mass during our study was the regional factor (45 %), followed by traffic (20 %), oil/incineration (17 %), ships (9 %), road dust (7 %), and sea salt (2 %).

Associations between asthma symptoms and PMF source factors

With the PMF source factors, univariate models for cough showed significant, positive associations with the regional

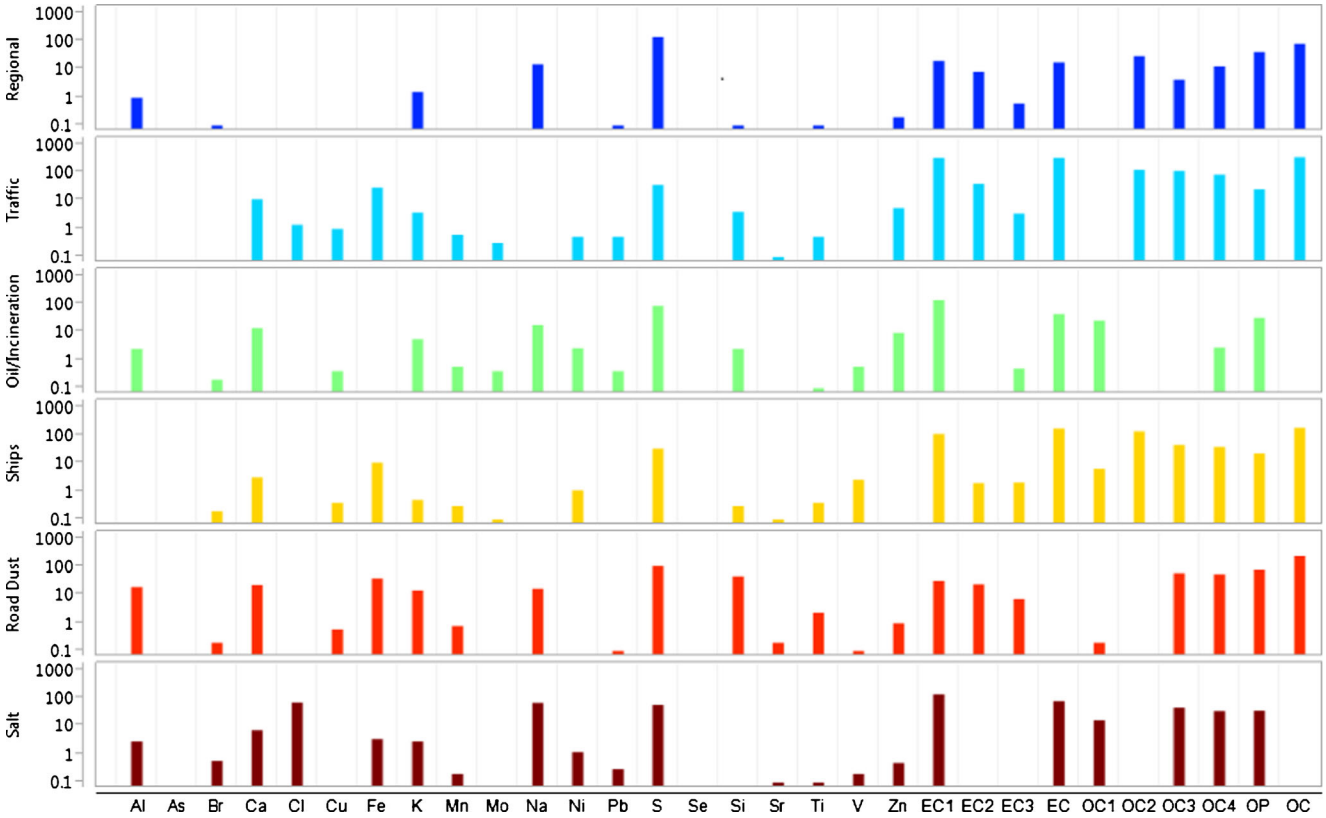

Fig. 1 Factor loadings

(lags 0, 1) and salt (lags 3, 0–3) factors, as shown in Fig. 2a. When results were adjusted for ozone, the salt lag 0–3 association disappeared (Fig. 2b). For wheeze symptoms, a significant positive association with the regional factor (lag 1) and a significant negative association with the oil factor (lag 0) were observed. Adjustment for ozone did not change the overall findings.

Associations between asthma symptoms and source tracers

Tracers were established based on their enhanced loadings onto, and correlations with, source factors, as described previously. Results for cough (Fig. 3a) indicate statistically significant, positive associations between cough symptoms and S (lag 1), K (lag 3), OC (lag 1), and pyrolized organic carbon (lag 1). Significant negative associations were observed for Fe (lag 2) and Si (lags 2 and 0–3). Adjusting for ozone resulted in a new significant positive association between cough and K (lags 2 and 0–3). The sulfur and OP associations with cough were no longer significant (Fig. 3b).

Wheeze symptoms were significantly and positively associated with K (lags 3 and 0–3) and S (lags 1 and 0–3), and negatively associated with Zn (lag 0) (Fig. 3a). Ozone adjustment resulted in the lag 1 association with S disappearing; otherwise, there were no changes (Fig. 3b).

Two-pollutant models with sulfur and either OC or OP were run in an attempt to disentangle the effects of the "regional" factor. No significant associations were observed (data not shown), and cough and wheeze results were virtually identical. In models unadjusted for ozone, a joint model with S and OC appeared to show a slightly more dominant effect of S; however, once ozone-adjusted, this effect disappeared and the associations were similar in magnitude. Joint models with S and OP yielded associations of similar magnitude for each pollutant whether the model was adjusted for ozone or not. Two-pollutant models with OP and OC tended toward stronger associations with OP than OC; however, again, none reached statistical significance.

Associations between asthma symptoms and carbon fractions

Very few significant associations were observed for EC and OC fractions (data not shown). Significant negative associations were found for EC2 (lag 0–3), EC3 (lag 2), and EC3 (lag 0–3) in cough models unadjusted for ozone; with adjustment, the EC2 (lag 0–3) and EC3 (lag 2) negative associations remained. As discussed above, we found a significant positive association for OP at lag 1 for cough, but once adjusted for ozone, this association became nonsignificant. No significant associations were observed between carbon fractions and wheeze symptoms.

Table 3 Correlation matrix for PM constituents and identified PMF source factors

	Regional	Traffic	Oil/incineration	Ships	Road dust	Salt
Al	0.35	0.16	0.18	0.45	0.82	0.32
As	0.16	0.01	−0.06	0.10	0.10	−0.07
Br	0.36	0.26	0.36	0.53	0.29	0.48
Ca	−0.11	0.40	0.73	0.42	0.41	0.56
Cl	−0.15	0.27	0.39	0.34	0.09	0.99
Cu	0.17	0.68	0.28	0.50	0.33	0.38
Fe	0.23	0.74	0.00	0.60	0.61	0.29
K	0.38	0.27	0.22	0.33	0.44	0.28
Mn	−0.02	0.41	0.58	0.42	0.31	0.41
Mo	−0.26	0.27	0.76	0.16	−0.03	0.40
Na	0.51	0.10	0.13	0.31	0.20	0.33
Ni	−0.26	0.17	0.85	0.39	0.09	0.55
Pb	0.23	0.41	0.37	0.30	0.17	0.33
S	0.94	0.23	−0.14	0.43	0.36	0.03
Se	0.23	−0.06	0.03	0.13	0.09	0.03
Si	0.22	0.21	0.04	0.40	0.96	0.17
Sr	0.35	0.23	−0.01	0.36	0.33	0.18
Ti	0.37	0.40	−0.01	0.60	0.82	0.27
V	0.18	0.21	0.33	0.95	0.32	0.45
Zn	−0.28	0.33	0.90	0.12	−0.04	0.45
EC1	0.12	0.66	0.41	0.48	0.17	0.50
EC2	0.31	0.23	−0.18	0.10	0.14	−0.17
EC3	0.17	0.11	−0.08	0.13	0.17	−0.10
EC	0.20	0.68	0.34	0.48	0.20	0.42
OC1	−0.24	−0.01	0.28	0.01	−0.04	0.16
OC2	0.43	0.33	−0.26	0.41	0.20	0.02
OC3	0.25	0.48	−0.17	0.37	0.26	0.18
OC4	0.40	0.54	−0.03	0.50	0.34	0.27
OP	0.65	0.24	−0.01	0.42	0.35	0.14
OC	0.47	0.45	−0.13	0.50	0.32	0.18

Discussion

We applied PMF to an air quality dataset in New York City and identified several source factors, which were then used in health outcome analyses. We found that asthma cough and wheeze symptoms were most strongly associated with regional and salt factors, and some of the tracer elements loading onto these factors. Associations with elemental and organic carbon fractions were mostly nonsignificant.

We carried out tracer analyses to evaluate consistency with source factor results. These tracer analyses compared generally relatively favorably to the source factor analyses, but there were some exceptions. For example, with the ozone-adjusted results, we observed a significant positive association between cough and K, but significant negative associations with Si. Both K and Si loaded onto the same PMF factor (road dust) in our analysis, so these results are difficult to interpret, especially given that we did not observe an association with the road dust factor itself. However, the correlation between K and the road dust factor was quite low (0.44), suggesting that there are other sources of this element, such as wood burning (e.g., Verma et al. 2009).

With wheeze, again significant positive associations were observed with K, but no associations were found for Si. We also found a positive association for S and a negative association for Zn, the latter which was a tracer for an oil/incineration factor. PMF factor results showed a positive association with the regional factor and a negative association with the oil/incineration factor, both of which are consistent with these tracer findings. If component-specific analyses support source factor analyses, we may have more confidence in the overall results. Several authors have demonstrated the value of this approach (e.g., Sarnat et al. 2008; Chen et al. 2010; Kamal et al. 2011; Rohr et al. 2011). On the other hand, as Ito et al. (2004) point out, if the *mixture* of PM components from a given source is the causal agent, then results of analyses using source-apportioned data may not be consistent with those using individual constituents. One of the challenges with source apportionment in general is the lack of consistency between factors named in different studies, both temporally and geographically. A factor named in one study may not compositionally resemble the same factor in another study, making it difficult to compare results across studies to look for consistency.

PMF resolved a factor that we termed "salt" due to its high loading with both sodium and chlorine; in health outcome analyses this factor was associated with increased cough at lags 3 and 0–3. In addition, tracer analyses using Na as a marker of salt resulted in a significant positive association at lag 1. However, after adjustment for ozone, the only significant finding for both the source factor and tracer analyses was for the salt factor at lag 0–3. This may be due to the fact that air masses derived from the south over the Atlantic Ocean contain higher ozone (Park et al. 2007) and are also Na-enriched; therefore, this is likely an "ozone effect" that disappears when controlling for that pollutant. Almeida et al. (2013) showed using back trajectory analysis that air masses that originate

Table 4 PM mass attributed to each factor

PMF factor	% Contribution	Average mass contribution ($\mu g/m^3$)
Regional	45	5.1
Traffic	20	2.2
Combined oil/incineration	17	1.9
Ships	9	1.0
Road dust	7	0.7
Salt	2	0.3

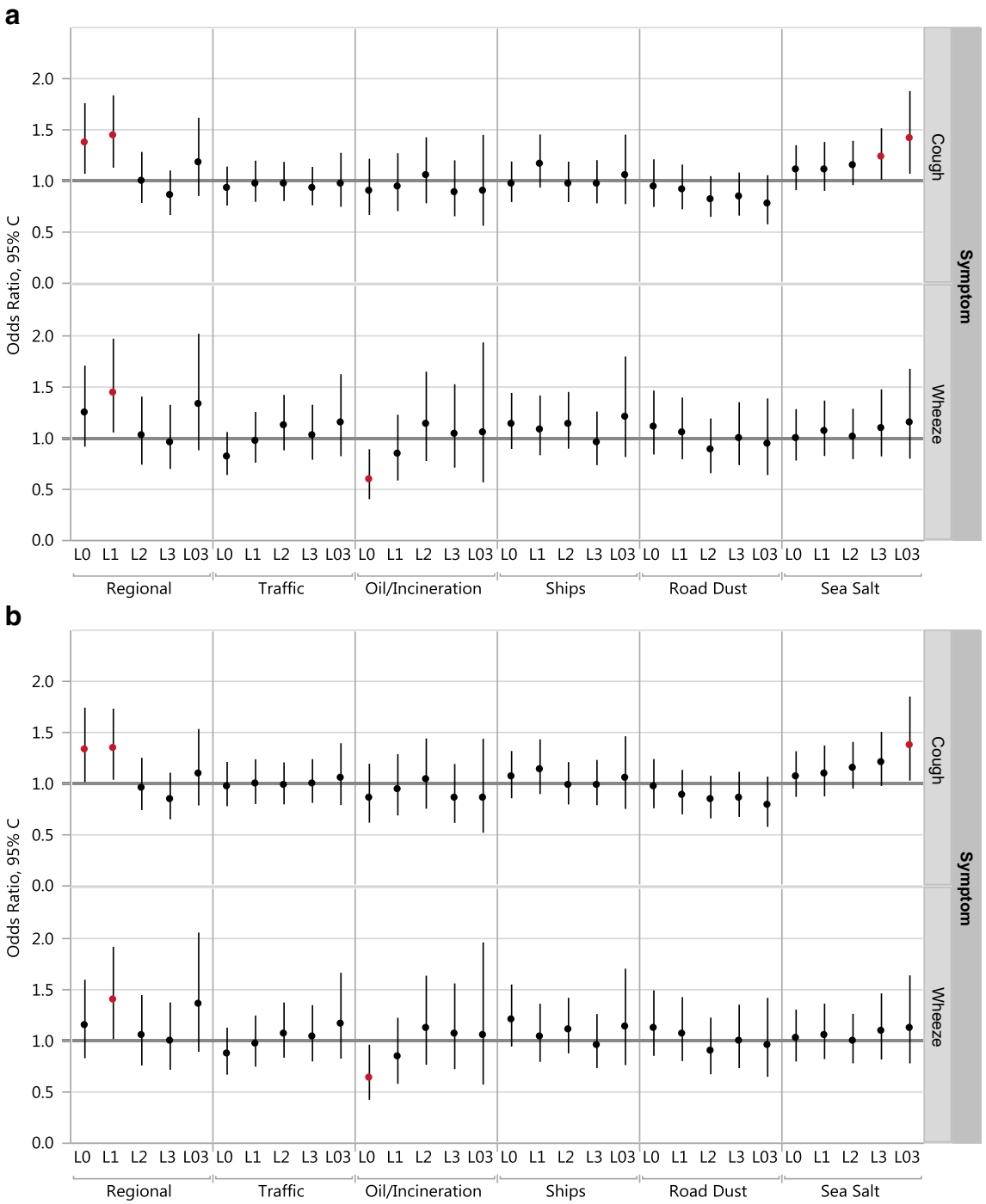

Fig. 2 Associations between cough and wheeze symptoms and PMF source factors. **a** Model adjusted for gender, race, season, temperature, and relative humidity. **b** Model adjusted for gender, race, season, temperature, relative humidity, and ozone

from the ocean contain significantly lower sulfate, nitrate, and ammonium—all of which are associated with anthropogenic sources and secondary production mechanisms—but significantly higher Na. However, in contrast, Jamason et al. (1997) found that springtime maritime tropical air masses, which presumably originate from the ocean, contained high pollutant concentrations (NO_2, total suspended particulate, and ozone). Moreover, these air masses were associated with increased hospital admissions for asthma in New York City. In Boston, Park et al. (2007) also found that air masses originating from the south, over the ocean, contained some of the highest pollutant concentrations, including sulfate and ozone.

The factors related to oil and ships merit specific discussion. Many studies (e.g., Lippmann et al. 2006) have suggested that elevated nickel and vanadium in the New York City are both related to residual oil combustion for space

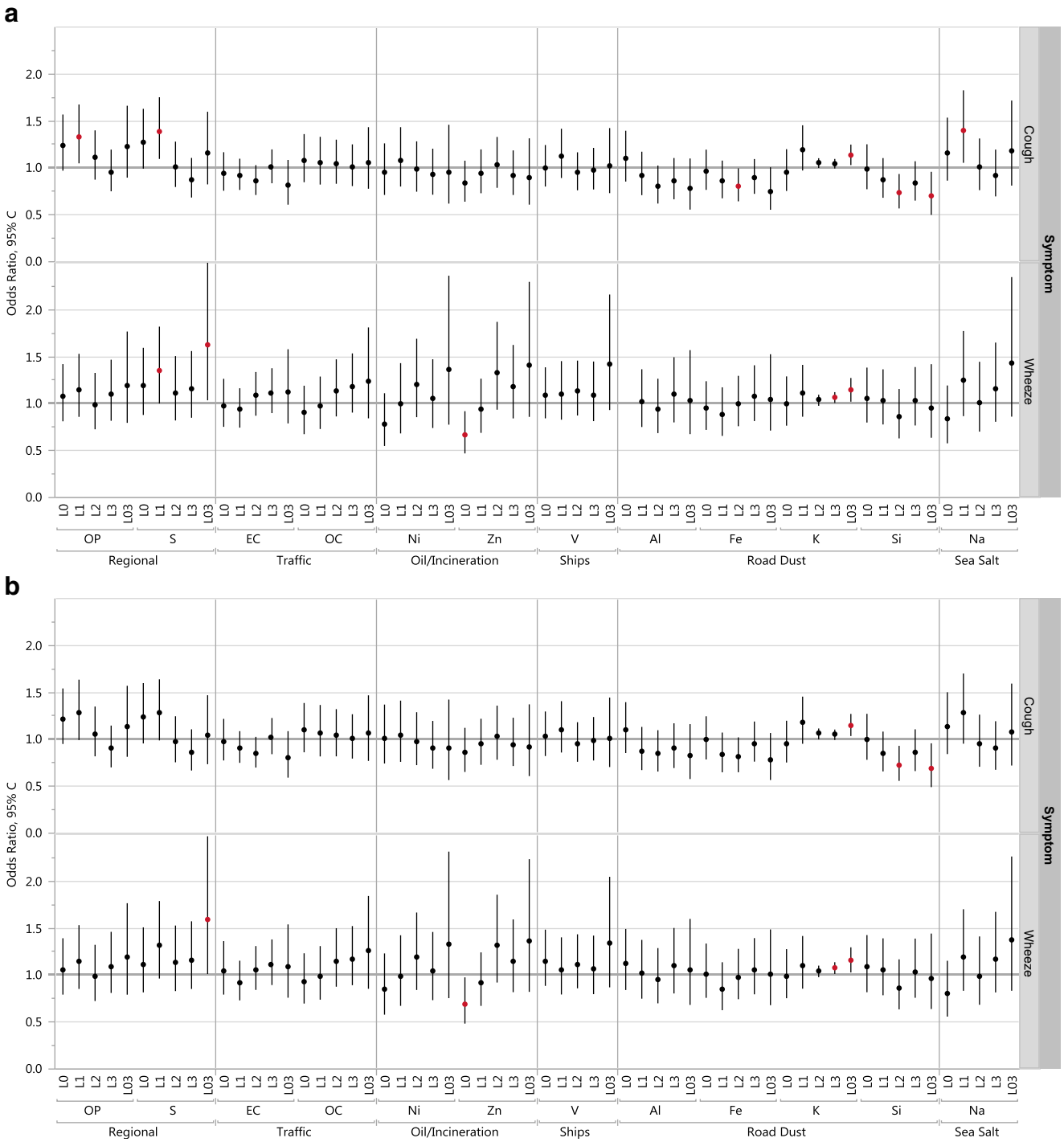

Fig. 3 Associations between cough and wheeze symptoms and tracer elements. **a** Model adjusted for gender, race, season, temperature, and relative humidity. **b** Model adjusted for gender, race, season, temperature, relative humidity, and ozone

heating. However, a study that involved measurement of these elements at 10 sites throughout NYC in both summer and winter showed poor correlation between Ni and V in both seasons (Peltier and Lippmann 2010). These authors suggested that Ni is primarily from space heating/oil, but V is mainly derived from the Port of New York. Our results are consistent with this premise; the correlation between Ni and V was 0.57 over the entire study period, but the correlation between the "combined oil/incineration" source factor and V was low (r=0.33). In contrast, the correlation between Ni and the oil factor was higher at 0.85. The "ships" factor was highly correlated with V (0.95) but not with Ni (0.39).

We found that a regional $PM_{2.5}$ source factor, and its primary component sulfur, was associated with asthma

symptom exacerbation in our cohort. We were interested in the composition of this factor to help determine its potential source(s). Upwind coal-fired power plants are likely to contribute to the factor, as evidenced by the high loading of S, which is primarily derived from the oxidation of SO_2 from coal combustion to sulfate. Primary metal sulfates from local sources such as smelters and sources burning residual oil can also be important in some areas (Huffmann et al. 2000). Other pollutants that showed moderate-to-high correlations with the regional factor included pyrolized carbon (r=0.65), ozone (r=0.55), and Na (r=0.51). In the TOR carbon fraction analysis, OP represents the heaviest, largest compounds that have undergone the most atmospheric processing; the correlation of OP with the regional factor suggests that upwind sources also include organic material. This material likely reflects secondary organic aerosol formation from both biogenically (e.g., terpenes emitted from vegetation) and anthropogenically derived (e.g., mobile sources) volatile organic compounds. These pollutants have undergone photochemical processes that may have rendered them more reactive and potentially more toxic. The fact that ozone is also correlated with the regional factor is consistent with an air mass comprised of secondary pollutants. We did not observe any significant associations when two-pollutant cough models were run with S along with either OC or OP, suggesting that neither component dominates the effect.

Other investigators have attempted to identify PM sources in New York City. Qin et al. (2006) applied PMF to air quality data at four Speciation Trends Network sites in the NYC area as well as an upwind background site. Source factors common to all five sites included secondary sulfate, secondary nitrate, soil, and aged sea salt. Oil combustion was identified at four of the sites, and at one site appeared to also show an influence from ship emissions. Motor vehicles were apportioned onto two factors (gasoline and diesel) at three sites. Li et al. (2004) also used PMF and identified secondary sulfate, secondary nitrate, motor vehicle emissions, road dust, sea salt, and oil combustion. Overall, our PMF results compare favorably, except that we did not identify a secondary nitrate factor, likely in large part because we did not have nitrate data.

Our health outcome findings are somewhat different than those from similar panel studies. Gent et al. (2009) found asthma symptoms in children living in New Haven, CT, USA, to be associated with traffic and road dust factors, and most of the components loading onto these factors (e.g., EC, Cu, Si, Al), as well as K (a marker of biomass combustion in the study) and V (tracer for oil combustion). We also found a positive association with K; however, in our study this element loaded onto a road dust factor and was therefore considered a tracer of that source. However, while Gent et al. did not observe associations with regional pollution (using S as a tracer) or with sea salt, we did observe such associations. In a study of 78 adult asthmatics in Helsinki, Finland, Penttinen et al. (2006) found decrements in pulmonary function to be most strongly and consistently associated with local traffic sources, as identified by high loadings of nitrogen oxides (NO_x), $PM_{2.5}$ absorption coefficient, ultrafine, and accumulation mode particle numbers combustion, although some positive associations were observed for the long-range transport factor, and negative associations were observed for a soil factor.

Studies evaluating respiratory symptoms in New York City have varied in the PM constituents or sources associated with health outcomes. For example, Patel et al. (2009) reported increased probability of wheeze in young children 0–24 months of age in NYC to be associated with nickel and vanadium, while cough was associated with EC. Patel et al. (2010) found BC to be associated with a variety of respiratory symptoms, while Lall et al. (2011) observed hospital admissions for respiratory causes in Manhattan to be associated with a steel-metal works source factor that was enriched in manganese. Finally, Spira-Cohen et al. (2011) reported significant associations between personal EC and cough and wheeze in Bronx children with asthma; no significant associations were observed with $PM_{2.5}$ mass or sulfur. As with the asthma panel studies discussed above, our findings differed from these studies.

A unique feature of our study was the collection and inclusion of IMPROVE/TOR carbon fractions (EC1, EC2, EC3, OC1, OC2, OC3, OC4, and OP). To our knowledge, this is the first use of these fractions in an air pollution epidemiological setting. We attempted to include the thermally resolved carbon fractions in the PMF analysis; however, this resulted in nonconvergence. Therefore, to estimate their loading profiles on the predicted sources, the carbon fraction concentrations were regressed on the estimated source contributions. It should be noted that there is significant noise in this approach, particularly in light of many negative values in the OC fraction dataset. When we used the fractions in the health outcome analyses, few significant associations were observed. These included OP, which was significantly positively associated with cough in models unadjusted for ozone, and two EC fractions that were negatively associated with cough. Given that EC and OC associations were uniformly nonsignificant, these findings are not unexpected.

The limitations of our study include the use of central site monitoring data to represent subject exposures. Spatial and temporal variability varies among pollutants, with regional pollutants such as secondary sulfate tending to be more spatially homogeneous. Ito et al. (2004) found that estimated source-apportioned $PM_{2.5}$ mass in New York City showed the highest monitor-to-monitor correlation (three monitors several miles apart) for the secondary aerosol factor, while the correlation for the more local traffic-related factor was more variable. This same study reported that the strongest temporal correlations across the three sites were for PM

components related to secondary aerosols (i.e., sulfate and ammonium). Because more exposure error leads to increased nondifferential exposure misclassification that can bias results to the null, this issue of differential measurement error among pollutants and source factors needs to be considered when interpreting results. For example, it will generally be easier to detect an association with a component with less exposure error, such as sulfate or secondary organic aerosol, than a component with more exposure error, like elemental carbon. This is a particular issue when utilizing central site data to represent population exposures. Another important study limitation is one of multiple comparisons; when many statistical tests are done—as with this study—there is an increased likelihood that significant positive or negative associations will be observed due to chance. Statistical power may also be an issue with our relatively small-sized cohort. Other study limitations include errors in PMF model predictions, and "factor smearing," which refers to unclear separation between factors due to the same component being present on multiple factors.

Overall, we found that salt and regional source factors were associated with asthma exacerbation in a high-risk cohort of children residing in New York City. In this study, the regional factor was comprised of sulfate as well as carbon-containing PM, the latter which is likely derived from both anthropogenic and biogenic sources.

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