The Influence of Traffic on Air Quality in an Urban Neighborhood: A Community–University Partnership

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Objectives. We evaluated the spatial and temporal patterns of traffic-related air pollutants in an urban neighborhood to determine factors contributing to elevated concentrations and to inform environmental justice concerns.

Methods. In the summer of 2007, we continuously monitored multiple air pollutants at a community site in the Mission Hill neighborhood of Boston, Massachussetts, and local high school students conducted mobile continuous monitoring throughout the neighborhood. We used regression models to explain variability in concentrations, considering various attributes of traffic, proximity to major roadways, and meteorology.

Results. Different attributes of traffic explained variability in fixed-site concentrations of ultrafine particles, fine particulate matter, and black carbon, with diurnal patterns and meteorological effects indicative of a greater local effect on ultrafine particles and black carbon. Mobile monitoring demonstrated that multiple traffic variables predict elevated levels of ultrafine particles, with concentrations of ultrafine particles decreasing by 50% within 400 meters of 2 major roadways.

Conclusions. Unlike fine particulate matter, ultrafine particles demonstrate significant spatial and temporal variability within an urban neighborhood, contributing to environmental justice concerns, and patterns can be well characterized with a community-based participatory research design. (*Am J Public Health.* 2009;99:S629–S635. doi:10.2105/AJPH.2008.149138)

In urban settings, exposure to traffic can be a significant environmental justice issue—when low-income or minority communities suffer disproportionate exposures to environmental toxins.[1] Many traffic-related primary air pollutants decrease in concentration rapidly as a function of distance from the roadway,[2] and low-income and minority populations often live disproportionately close to major roadways.[3,4] Living near truck routes or major roadways has been associated with increased rates of asthma symptoms[5–7] or hospitalizations.[8,9] The effect of traffic-related pollutants is greater among low-income individuals[10] and those with greater exposure to violence.[11] These findings are in agreement with the hypothesized pathways through which low-income populations would be differentially affected by air pollution—exposure differentials related to property values and facility siting practices, susceptibility directly related to social position, and susceptibility related to predisposing health conditions[12]—which would all be present when one considers urban traffic impacts.

Evaluation and mitigation of traffic-related environmental justice issues is complicated by multiple factors, including the lack of adequate air quality data. Few air pollution monitors are found within urban neighborhoods, and the limited spatial coverage of the available monitors precludes identification of "hot spots." Studies have deployed passive samplers to capture spatial variability in pollutants such as nitrogen dioxide,[13–15] but these integrated measures cannot capture the short-term dynamics associated with traffic. Communities are not only interested in knowing where air pollution levels are high, but also whether this is because of idling vehicles, rush hour back-ups, or other factors beyond total traffic volume.

To better characterize small-scale spatial variability in traffic-related air pollution, studies have used portable continuous monitors in a geographic information system framework. One effort in a Boston neighborhood[16] found elevated particle-bound polycyclic aromatic hydrocarbon (PAH) concentrations with proximity to a major bus terminal, with evidence of both PAH and fine particulate matter ($PM_{2.5}$) elevations during morning rush hour. However, this study lacked extensive traffic or meteorological data. A study in New York City[17] demonstrated significant variability in black carbon concentrations associated with local diesel traffic, but only characterized a limited number of sites. Both studies involved communities in study design and sampling within a community-based participatory research (CBPR) framework, but there remains a need for more intensive characterization of spatiotemporal patterns of multiple traffic-related pollutants for communities. In particular, neither study included ultrafine particulate matter, which may show more significant spatial gradients than $PM_{2.5}$.[2]

We focused our air quality characterization in Mission Hill, part of the Roxbury neighborhood of Boston. Mission Hill is a racially/ethnically diverse neighborhood (19% Hispanic, 20% non-Hispanic Black or African American, 14% Asian, and 47% non-Hispanic White or multiracial), with 36% of residents below the poverty level.[18] Across all Boston neighborhoods, Roxbury has the highest asthma hospitalization rate for children younger than 5 years, with elevated rates of infant mortality and age-adjusted mortality.[19]

In addition, Mission Hill abuts the hospitals and schools in the Longwood Medical Area, which induce substantial traffic and have a projected workforce growth of 24% between 2003 and 2013.[20] The epicenter of Longwood Medical Area–related traffic is near the intersection of Tremont and Francis streets (the street changes names at the intersection) and Huntington Avenue (Figure 1), which has been characterized as a significant congested intersection,[21] and is proximate to 3 large housing developments with numerous vulnerable

Note. This map shows the stationary sites along Huntington Ave and Tremont and Francis St and the location of the fixed site at the Mission Hill Health Movement.

Figure 1—Map of our monitoring region (shaded area), with mean ultrafine particle counts by road segment: Huntington Avenue, Tremont and Francis Streets, and the Mission Hill Health Movement, Boston MA, 2007.

individuals, several elementary schools, day care programs, and recreational space. Because of the confluence of sensitive subpopulations, potentially elevated concentrations, and continued growth of the Longwood Medical Area, community groups such as the Mission Hill Health Movement have become concerned about local air quality and the health and environmental justice implications.

To address these concerns, a community–university research partnership was established that jointly developed a study to characterize air quality patterns and establish a baseline for comparison as traffic volumes increase. Monitoring equipment was placed at the Mission Hill Health Movement office, and mobile monitoring protocols were developed utilizing local high school students to conduct the sampling. Both mobile and fixed-site sampling involved multiple continuous measurements, including ultrafine particle counts, $PM_{2.5}$, traffic, and meteorology. We hypothesized that these protocols coupled with a regression-based framework accounting for traffic counts, speed, and composition, wind speed and direction, and proximity to major roadways would allow for the traffic contribution to community air quality to be well-characterized and useful for future development of intervention strategies.

METHODS

To characterize air pollution patterns in Mission Hill, we utilized a combination of mobile and fixed-site monitoring coupled with traffic characterization. Fixed-site monitors were placed at the Mission Hill Health Movement office on Tremont Street in the center of our domain (Figure 1), and mobile monitoring followed defined routes across most of Mission Hill. Six high school students, recruited through the Harvard School of Public Health Research Apprenticeship Program, Project Success at Harvard Medical School, and local high schools and community organizations, represented the primary field staff, supervised by the authors. They received training on air pollution monitoring, project protocols, and general issues in scientific inquiry.

Fixed-Site Monitoring

The monitors installed at the Mission Hill Health Movement office (Figure 1) collected continuous measurements aggregated to 10-minute averages from July through September 2007. Monitors were placed indoors with tubing running outside through a polyvinyl chloride pipe, collecting measurements approximately 4 meters above the ground. The length of tubing (2 m to 5 m across instruments) necessitated by the building configuration contributed to some particle losses, but we utilized Tygon polyvinyl chloride and polytetrafluoroethylene tubing (Saint-Gobain, Courbevoie, France) to minimize deposition, and our measurements are interpretable in a relative sense (examining diurnal patterns and predictors of fixed-site concentrations).

Measurements at the fixed site included a water-based condensation particle counter for ultrafine particles (CPC Model 3781, TSI, Shoreview, MN), a laser photometer for $PM_{2.5}$ (TSI DustTrak 8520), a photoelectrical aerosol sensor for particle-bound PAHs (PAS 2000CE, EcoChem Analytics, League City, TX), an aethalometer for black carbon (Model AE42, Magee Scientific, Berkeley, CA), and a nitric oxide (NO) monitor (Model 400, 2B Technologies, Boulder, CO). For $PM_{2.5}$, daily concentration data were also collected from a nearby Environmental Protection Agency monitor (in Dudley Square, approximately 1.5 km from the fixed site).

A Weather Wizard III (Davis Instruments, Hayward, CA) was set up on the roof of the 1-story Mission Hill Health Movement office, with the wind vane affixed to the side of a ventilation stack pipe in a location that minimized building envelope effects and shielding by neighboring buildings. This instrument collected temperature, wind speed, and wind direction. A HOBO Pro H08-032-IS (Onset Computer Corporation, Pocasset, MA) was affixed next to the wind vane and measured temperature, relative humidity, and dew point.

Traffic Monitoring

To capture real-time traffic data, we used Trax I Plus traffic counters (JAMAR Technologies, Horsham, PA), which use a set of tubes laid across the roadway to record traffic volume and, under certain configurations, speed and composition. Counters were placed on both Huntington Avenue and Tremont Street

(Figure 1). Huntington Avenue is a 4-lane, 2-directional street with a Massachusetts Bay Transportation Authority train line running in the median. Given this configuration and available instrumentation, we could not capture traffic in both directions and focused on traffic toward downtown Boston (traveling northeast). This counter only captured traffic volume data. A second traffic counter was placed in front of the Mission Hill Health Movement office, capturing vehicle counts and, on a subset of dates, vehicle counts by axle class and by speed.

Mobile Monitoring

The high school students conducted mobile monitoring in July through August 2007 as 3 teams of 2 students. Each team carried a set of equipment in a backpack and messenger bag—PAS 2000CE, DustTrak 8520, and CPC 3781 with portable battery and casing, all of which recorded 1-minute average concentrations. The teams were also given a Global Positioning System (GPS; Model 60CSx, Garmin, Olathe, KS) and a clipboard with traffic monitoring worksheets and informational pamphlets to hand out to interested community members.

Sampling was performed in two 2-hour shifts each day between 9:00 AM and 5:00 PM, with shift length dictated by battery life and the size of the monitoring region. Four mobile routes were established throughout the neighborhood and sampled forward and backward, along with 3 sets of 3 parallel routes to separate spatial and temporal variability. The parallel routes consisted of 1 route on 1 side of a main road and 2 routes on 2 parallel roads on the same side of the main road. Also, 25 stationary monitoring sites were located at varying distances from the 2 major roadways (Figure 1).

For most shifts, each group conducted 1 hour of stationary sampling and 1 hour of mobile sampling. During stationary sampling, the groups characterized traffic in 4 different ways: (1) directly counting diesel and nondiesel vehicles for 5-minute intervals, (2) characterizing traffic flow every 30 seconds (e.g., light free-flow, start-and-stop, gridlocked), (3) setting waypoints on the GPS whenever traffic was backed up beyond where the group was sampling, and (4) logging the presence of idling vehicles. The groups also logged atypical source activity, including smokers, construction, or grilling. During mobile sampling, not all forms of traffic characterization were practical, so the groups only logged idling vehicles and atypical source activity. To avoid damage to equipment, mobile monitoring was cancelled on days with threat of rain.

Statistical Analysis

We considered the 5 pollutants from the fixed site and 3 from the mobile monitoring as candidate outcome variables. Various measures from the traffic counter in front of the fixed site were used to predict fixed-site concentrations. Vehicle counts classified by axle length following the 14 category Federal Highway Administration Type F Vehicle Classification Scheme[22] were aggregated to generally represent nondiesel-fueled vehicles (e.g., cars, motorcycles, pickups, vans) and diesel-fueled vehicles (e.g., buses, heavy-duty trucks), recognizing that some misclassification was likely because of buses fueled by compressed natural gas and other alternative fuels. Vehicles that were uncategorized were apportioned on the basis of counts in each category during the corresponding time period. Vehicle counts by speed were grouped as traveling faster than 15 miles per hour and 15 miles per hour or slower.

We also considered temperature, relative humidity, wind speed, and wind direction as covariates. Wind speeds were collapsed into 3 bins: 0 to 0.5 meters/second, 0.5 to 1 meters/second, and more than 1 meter/second. Wind direction was categorized as upwind, downwind, or parallel relative to Tremont St. These 3 wind direction variables were interacted with the 3 wind speed variables, creating 9 wind categories. Thus, our fixed-site models separately consider the 3 alternative traffic-counter measures, controlling for temperature, relative humidity, and wind speed and direction. We present fixed-site models for ultrafine particles, $PM_{2.5}$, and black carbon and not PAHs and NO because PAH measurements frequently were below the effective limit of detection of the instrument (30% of values higher than 10 ng/m^3), and instrument problems prevented collection of NO concurrent with traffic data. We also evaluated whether autocorrelation in our continuous measurements had an influence on our findings by applying an autoregressive model of order 1 (AR1) autocorrelation structure.

For our mobile monitoring, we developed separate models for the stationary measurements and for mobile and stationary monitoring combined. We had insufficient contemporaneous automatic traffic counter data, so in the former case, we considered each of the 4 forms of field staff traffic characterization as predictors, controlling for temperature, relative humidity, and wind speed and wind direction relative to the roadway on which the monitoring was occurring, and distance from the other major roadway. In the latter case, we considered distance to each of the major roadways as predictors, controlling for temperature, relative humidity, and wind speed and wind direction relative to each of the 2 major roadways, and also considered idling vehicles. In both cases, we tested the influence of an AR1 autocorrelation structure within a repeated measures model by sampling day and bag. We developed models for both ultrafine particles and $PM_{2.5}$, which were run with R version 2.7.1.

RESULTS

There was significant diurnal variability in multiple pollutants at our fixed site. Black carbon featured a peak during morning rush hour with a steady decline in concentrations throughout the day, whereas ultrafine particles demonstrated an earlier increase and elevated concentrations through the early afternoon. In contrast, $PM_{2.5}$ had less diurnal variability (Figure 2). Our $PM_{2.5}$ measurements were reasonably correlated with measurements from the nearby Environmental Protection Agency monitor (Pearson correlation coefficient of 0.75), especially in light of differences in instrumentation.

Traffic on Tremont Street showed an atypical pattern. Counts were fairly steady after the morning rush hour through the afternoon, with an increase in slow-moving vehicles in the middle of the day and the greatest hourly volume occurring between 7:00 PM and 8:00 PM (Figure 2). Diesel vehicle counts increased during the morning rush hour and peaked at

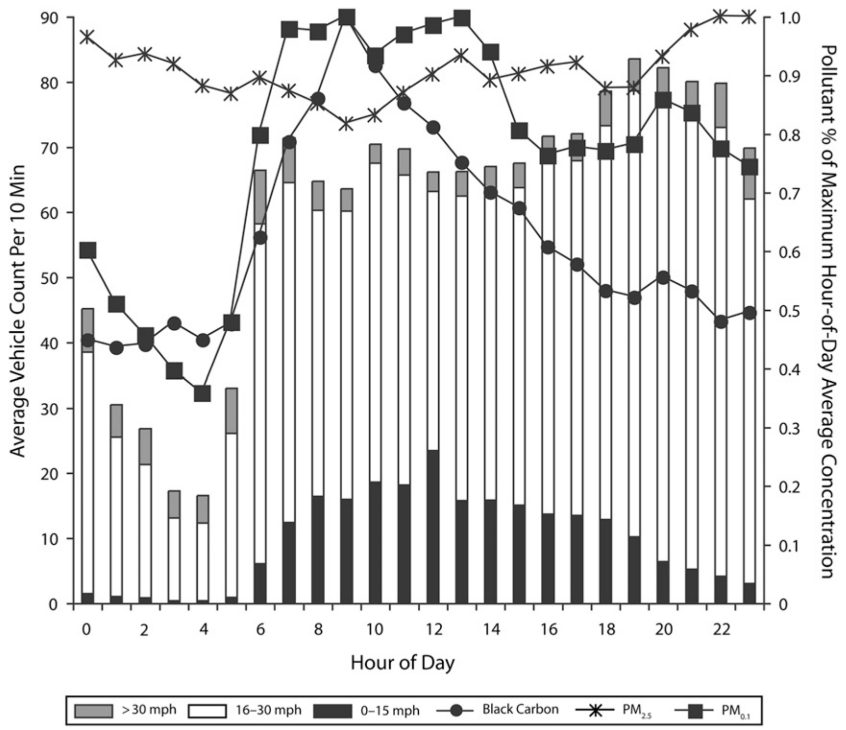

Figure 2—Diurnal patterns of traffic volume and pollutant concentrations at the fixed site, with pollutant concentrations presented as hourly averages throughout the monitoring campaign as a percentage of the maximum hour-of-day average by pollutant: Mission Hill Neighborhood, Boston, MA, 2007.

noon, with a slow decline for the rest of the afternoon (results not shown).

When we controlled for temperature, relative humidity, and wind speed and direction, total vehicle count was significantly associated with ultrafine particles and $PM_{2.5}$ at the fixed site with a positive but insignificant association with black carbon (Table 1). When we stratified vehicle counts by type, statistical power was limited given generally low diesel counts, but there was evidence of a greater effect of diesel vehicles on ultrafine particles and black carbon, whereas nondiesel vehicles were significantly associated with $PM_{2.5}$ (Table 1).

When we stratified vehicle counts by speed, vehicles traveling 15 mph or slower were significantly associated with ultrafine particles and black carbon, whereas vehicles traveling faster than 15 mph were significantly associated with $PM_{2.5}$. Across all models, concentrations were significantly greater under downwind conditions for ultrafine particles and black carbon, with higher concentrations observed in the lower wind speed categories (results not shown). In contrast, for $PM_{2.5}$, the effect of local wind speed and direction was inconsistent and less statistically significant, indicative of a lesser local contribution to measured concentrations. Use of an AR1 autocorrelation structure had no influence on our conclusions, with minimal changes in regression coefficients and minor increases in standard errors.

For our stationary and mobile monitoring analysis, the traffic flow log sheets were not predictive of concentrations and are not presented, but the other 3 methods of traffic characterization showed some predictive power (Table 2). On both roads, total vehicle counts were significantly related to increases in ultrafine particles, whereas $PM_{2.5}$ was only associated with counts on Tremont and Francis streets. When we stratified by vehicle type (results not shown), the models were more unstable given low diesel counts, but diesel counts had a greater effect on ultrafine particles than nondiesel counts, supporting our fixed-site models (Table 1). The total vehicle count regression model also indicated a significant effect of distance from roadway for ultrafine particles but not for $PM_{2.5}$ (Table 2). Traffic backups to the point of stationary monitoring and the presence of idling vehicles were associated with elevated ultrafine particle counts only on Tremont and Francis streets.

For the mobile monitoring, distance from each road was significantly negatively related to ultrafine particle concentrations, but demonstrated no predictive power for $PM_{2.5}$ (Table 2). The coefficients from the mobile monitoring model are similar to those from most of the stationary monitoring models and indicate that ultrafine particle counts drop approximately 1000 particles per centimeter cubed for each 50-meter increment away from each of the major roadways. Maps of mean ultrafine concentrations by road segment (Figure 1) show that most of the segments with elevated concentrations were along or proximate to the major roadways.

When terms for wind speed and wind direction were included in the mobile monitoring models, the traffic and distance main effects were robust, but the interactions with wind speed and wind direction generally lacked statistical significance and were difficult to interpret. Similarly, because of a relatively small sample size within bag and day, and some missing data, application of an AR1 model influenced the regression coefficients and standard errors and yielded uninterpretable models. As a result, these terms and methods were not included in the models in Table 2.

DISCUSSION

Our analysis demonstrated that a community-scale mobile monitoring protocol can determine both the spatial patterns of concentrations throughout a neighborhood and the attributes of traffic associated with elevated concentrations. Our models in Table 2 captured significant gradients as a function of distance from both key roadways for ultrafine particles but not $PM_{2.5}$, both with stationary

TABLE 1—Results for Fixed-Site Modeling, Adjusted for Temperature, Relative Humidity, and Wind Speed and Direction: Mission Hill Neighborhood, Boston, MA, July–September 2007

	Ultrafine Particles		$PM_{2.5}$		Black Carbon	
	Estimate	P	Estimate	P	Estimate	P
Total vehicle counts[a]	8.67	.032	4.09×10^{-5}	.022	1.92	.105
Counts by fuel type[b]						
Diesel vehicle count	96.95	<.001	-3.71×10^{-5}	.668	39.78	<.001
Nondiesel vehicle count	−6.43	.204	5.43×10^{-5}	.018	−4.51	.002
Speed[c]						
Vehicles driving ≤ 15 mph	93.18	<.001	-7.07×10^{-5}	.316	29.05	<.001
Vehicles driving > 15 mph	0.58	.89	5.90×10^{-5}	.002	−0.3	.806

Notes. $PM_{2.5}$ = fine particulate matter. Vehicle counts refer to number of vehicles per 10-min period.
[a]For ultrafine particles: n = 436; R^2 = 0.36. For $PM_{2.5}$: n = 437; R^2 = 0.19. For black carbon: n = 432; R^2 = 0.25.
[b]For ultrafine particles: n = 436; R^2 = 0.39. For $PM_{2.5}$: n = 437; R^2 = 0.19. For black carbon: n = 432; R^2 = 0.34.
[c]For ultrafine particles: n = 439; R^2 = 0.40. For $PM_{2.5}$: n = 440; R^2 = 0.19. For black carbon: n = 435; R^2 = 0.32.

and mobile measurements. Previous studies[2] have shown that ultrafine particle levels drop to 50% of the maximum concentration within approximately 100 meters to 300 meters of a major roadway (usually highways). Our mobile regression models imply that mean ultrafine concentrations drop from 32 000 particles per centimeter cubed at the intersection of the 2 roadways to 16 000 particles per centimeter cubed at a point 400 meters away from each of the major roadways. The slightly greater distance in our study is likely attributable to monitoring within an urban community with traffic on many side roads, including some large roads near the boundary of our domain.

TABLE 2—Results From Stationary and Mobile Monitoring, Adjusted for Temperature and Relative Humidity: Mission Hill Neighborhood, Boston, MA, July–September 2007

	Ultrafine Particles		$PM_{2.5}$	
	Estimate	P	Estimate	P
Vehicle counts[a]				
Total count on Huntington Ave	329.02	.002	5.84×10^{-6}	.918
Total count on Tremont/Francis St	369.03	.048	4.17×10^{-4}	<.001
Distance from Huntington Ave while on Tremont/Francis St	−49.18	<.001	-6.35×10^{-6}	.229
Distance from Tremont/Francis St while on Huntington Ave	−47.38	<.001	-8.23×10^{-7}	.912
Backups[b]				
Backups while on Huntington Ave	495.49	.826	-1.06×10^{-3}	.253
Backups while on Tremont/Francis St	5702.82	.003	-4.81×10^{-4}	.623
Distance from Huntington Ave while on Tremont/Francis St	−21.48	.014	6.99×10^{-6}	.052
Distance from T/F while on Huntington Ave	−14.9	.176	-1.09×10^{-5}	.042
Idling[c]				
Idling while on Huntington Ave	-4705.91	.112	-1.84×10^{-3}	.306
Idling while on Tremont/Francis St	9229.91	.01	-1.67×10^{-3}	.468
Distance from Huntington Ave while on Tremont/Francis St	−23.97	.006	7.38×10^{-6}	.039
Distance from Tremont/Francis St while on Huntington Ave	−19.05	.077	-1.08×10^{-5}	.037
Mobile monitoring[d]				
Distance from Tremont/Francis St	−18.49	<.001	2.41×10^{-6}	.572
Distance from Huntington Ave	−19.5	<.001	-3.20×10^{-6}	.332

Notes. $PM_{2.5}$ = fine particulate matter. Vehicle counts refer to number of vehicles per 1-min period, and distance is measured in meters.
[a]For ultrafine particles: n = 1710; R^2 = 0.08. For $PM_{2.5}$: n = 3363; R^2 = 0.22.
[b]For ultrafine particles: n = 2072; R^2 = 0.06. For $PM_{2.5}$: n = 4126; R^2 = 0.21.
[c]For ultrafine particles: n = 2076; R^2 = 0.06. For $PM_{2.5}$: n = 4127; R^2 = 0.21.
[d]For ultrafine particles: n = 3815; R^2 = 0.11. For $PM_{2.5}$: n = 9914; R^2 = 0.30.

The fixed-site analyses appear to show that slow-moving and diesel vehicles influence ultrafine particles and black carbon, whereas fast-moving and nondiesel vehicles influence $PM_{2.5}$. In addition, manual traffic counting, characterization of traffic backups, and monitoring of idling vehicles performed by field staff are predictive of elevated concentrations. Interestingly, the latter 2 traffic characterizations were only predictive of ultrafine particle counts on 1 of the 2 roadways, and total traffic counts significantly predicted $PM_{2.5}$ concentrations on that same roadway (both with mobile measurements and with automatic counts at the fixed site). This may be attributable to differences in traffic flow and composition, road width and local topography, or other local conditions, but generally emphasizes that different terms may serve as useful proxies for traffic impacts in different settings. Regardless, the utility of these terms indicates that community-based efforts to characterize traffic flows can be informative in determining hot spots in both space and time.

There are some key limitations in interpretation of our findings. The lack of significance for wind speed and wind direction terms in our mobile models is concerning, because of their physical linkage with atmospheric dispersion, and is likely attributable to the very low wind speeds measured in our study and the variability in wind fields within an urban area. We could have tested meteorological data measured at the airport or other sites, but it is unclear whether those adequately represent local-scale phenomena that may be present within complex urban terrain (including a large hill and tall buildings along the major roads).

Also, automated traffic count data were not available throughout the mobile monitoring period, given instrument limitations and missing data, which limits the predictive power of our mobile regression models. That being said, traffic volumes were fairly consistent between 9:00 AM and 5:00 PM (Figure 2), and our mobile regression models were robust in spite of these missing data. Our mobile regression models were sensitive to the approach for addressing autocorrelated measurements, but this is more likely related to missing data within shorter sampling sessions than inherent properties of the measurements because fixed-site regression outputs were insensitive to assumptions about autocorrelation. The partial autocorrelation of the residuals for both fixed-site and mobile models dissipated after 2 lagged observations, showing a small influence of autocorrelation. In general, missing data across multiple variables led to greatly reduced sample sizes for our multivariate regressions. Because these data appear to be missing at random, this does not influence our overall conclusions but clearly reduced our power to detect subtle effects or interactions among predictors.

In addition, it is possible that the traffic covariates had some measurement error or were proxies for other factors, so we cannot necessarily conclude (for example) that ultrafine particle concentrations are only influenced by diesel vehicles. Our regression models, including the significance of different forms of traffic characterization, may not be directly applicable to other cities, because of differences in traffic composition, meteorology, and urban topography. The fact that the mobile and fixed-site models are not contemporaneous and are affected by differences in measurement height and length of tubing limits the joint interpretation of their coefficients, but the general consistency in findings indicates the robustness of our models. Finally, because mobile monitoring occurred only during the summer during daytime hours, the spatial gradients may not be generalizable to all times of the year. For example, background concentrations of particulate sulfate are highest in Boston in the summer, which will tend to dampen spatial variability of $PM_{2.5}$. Additional monitoring during other seasons would clearly be warranted, although the use of high school students complicates intensive efforts during the school year.

In spite of these limitations, our study showed that continuous portable air-pollution monitoring, largely conducted by local high school students, can provide insight about air pollution patterns and the characteristics of traffic associated with air pollution. Monitoring campaigns can provide geospatial data that can be compared with population attributes or disease patterns, informing environmental justice considerations, and can more generally be used to help communities understand local air quality and develop mitigation strategies.

According to CBPR practices, results from this study have been disseminated directly to the Mission Hill Health Movement, community members, and the city of Boston, with some tangible impacts. For example, the Mission Hill Health Movement has initiated walking groups to increase physical activity rates among residents of Mission Hill, and our results can help determine which routes would minimize air pollution exposures. In general, the existence of significant spatial gradients for ultrafine particles within urban neighborhoods emphasizes the potential for environmental justice issues, especially with the presence of susceptible populations along major roadways, and the need for partnerships between researchers and community groups to characterize air pollution patterns in a manner that informs intervention strategies. ■

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Contributors

J.J. Buonocore supervised all aspects of data collection and led the statistical analyses. H.J. Lee contributed to design of the study, provided field staff supervision, and coordinated community outreach. J.I. Levy originated the study, led study design, and supervised statistical analyses and article preparation. All authors helped to coordinate field efforts and to review drafts of the article.

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Human Participant Protection

Human participant protection was not necessary for this research.

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