ENVIRONMENTAL HEALTH PERSPECTIVES
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http://dx.doi.org/10.1289/ehp.1206337

Received: 30 November 2012
Accepted: 26 September 2013
Advance Publication: 27 September 2013

National Institute of Environmental Health Sciences

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Short title: Air pollution and individual and neighborhood SES

Acknowledgement: The main MESA study was funded by the National Institutes of Health NHLBI (N01-HC-95159 through N01-HC-95165, N01-HC-95169), the MESA neighborhoods study was funded by NHLBI (R01 HL071759) and NIMHD (3P60MD002249-05S1) and the MESA air pollution study was funded by the US Environmental Protection Agency (R831697

STAR Grant). GSL was supported by NICHD (K01 HD067390). MSO was funded by NIEHS R01 016932. LS was funded by NIEHS (5 P50ES015915). JDK was funded by NIEHS (P30ES07033 and K24ES013195).

No competing financial interests to declare

Abstract

Background: Research has documented that low socioeconomic status (SES) and minority communities have higher exposure to air pollution. Few studies have simultaneously investigated the associations of individual and neighborhood SES with pollutants across multiple sites.

Objectives: We characterized the distribution of ambient air pollution by both individual and neighborhood SES using spatial regression methods.

Methods: The study population was 6,140 individuals from the Multi-Ethnic Study of Atherosclerosis (MESA). Year 2000 annual average ambient $PM_{2.5}$ and NO_x concentrations were calculated for each study participant's home address at baseline examination. Several individual and neighborhood (census tract-level) SES measures corresponding to the domains of income, wealth, education, and occupation were investigated. A spatial intrinsic conditional autoregressive model was used for multivariable analysis. Pooled and metropolitan area–specific models were examined.

Results: One unit increase in the z-score for family income was associated with 0.03 $\mu g/m^3$ lower $PM_{2.5}$ (95% CI: -0.05, -0.01) and 0.93% lower NO_x (95% CI: -1.33, -0.53) after adjustment for covariates. One standard deviation unit increase in the neighborhood's percentage of persons with at least a high school degree was associated with 0.47 $\mu g/m^3$ lower mean $PM_{2.5}$ (95% CI: -0.55, -0.40) and 9.61% lower NO_x (95% CI: -10.85, -8.37). Metropolitan area specific results exhibited considerable heterogeneity. For example, in New York, high SES neighborhoods were associated with higher concentrations of pollution.

Conclusions: We found statistically significant associations of SES measures with predicted air pollutant concentrations, demonstrating the importance of accounting for neighborhood- and individual-level SES in air pollution health effects research.

Introduction

A large body of observational studies has documented associations of air pollution with health outcomes including cardiovascular disease, pregnancy outcomes, and asthma and other respiratory problems in children (Brook et al. 2010; HEI 2010; Stieb et al. 2012). Because of the observational nature of much of the evidence, concerns are sometimes raised regarding the possibility of residual confounding by other factors. Socioeconomic status (SES) is a major concern as a cause of residual confounding because of its known links to many health outcomes (Adler and Stewart 2010) and because it is associated with air pollution exposures through class-based residential segregation and spatial clustering of air pollution sources (including traffic and point source emissions) (Gee and Payne-Sturges 2004; Mohai et al. 2009). Thus, understanding how SES and air pollution exposure are related is important when trying to infer causality based on statistical associations between air pollution and health. It also has implications for a rapidly growing area of research concerning the joint effects of air pollution and SES (among other social factors) on health outcomes (Clougherty and Kubzansky 2009; Morello-Frosch and Shenassa 2006). Lastly, characterizing the association between SES and air pollution exposures is important to understand the causes of disparities in many of the health conditions associated with air pollution.

A number of investigations have reported associations between air pollution and SES (Brulle and Pellow 2006). Few studies have evaluated associations between individual-level SES and air pollution (Marshall 2008). Others have examined community level factors such as area level poverty and educational attainment (Bell and Ebisu 2012; Brochu et al. 2011; Buzzelli and Jerrett 2007; Miranda et al. 2011; Yanosky et al. 2008). However, we are aware of only two studies that have simultaneously examined how both individual and neighborhood SES are related to air pollution (Cesaroni et al. 2010; Chaix et al. 2006). Both individual- and neighborhood-level SES constructs have been independently associated with health outcomes including cardiovascular disease (Diez Roux and Mair 2010). Evidence that both constructs are independently related to air pollution would support the need to adjust for both types of measures when estimating associations between air pollution and health, and would suggest that individual- and neighborhood-level socioeconomic disparities in health could be at least partly attributable to air pollution exposures.

Methodological challenges to characterizing the relation between SES and air pollution include the need to use modeling techniques that appropriately account for spatial autocorrelation (Brochu et al. 2011; Buzzelli and Jerrett 2007; Chaix et al. 2006; Jerrett et al. 2001; Yanosky et al. 2008), the need for geographic diversity (Bell and Ebisu 2012; Miranda et al. 2011), and the need for individual-level (as opposed to area-level) estimates of air pollution concentrations (Marshall 2008). Few studies of SES and air pollution have addressed these methodological issues.

A range of broader contextual factors including the degrees of residential segregation and the spatial location of various SES groups with respect to major sources of air pollution may modify the associations between SES and air pollution (Gee and Payne-Sturges 2004; Mohai et al. 2009). Although it is important to investigate these patterns across a range of geographic areas to properly assess heterogeneity in associations between SES and air pollution, many previous studies have been limited to a single site (Buzzelli and Jerrett 2007; Cesaroni et al. 2010; Chaix et al. 2006; Grineski et al. 2007; Jerrett et al. 2001; Marshall 2008; Molitor et al. 2011; Yanosky et al. 2008). Evidence of a lack of heterogeneity in associations between SES and air pollution would have important implications with regard to potential confounding by SES, and for understanding the extent to which health disparities are attributable to air pollution.

We used data from the Multi-Ethnic Study of Atherosclerosis (MESA), a large population based study conducted in several regions of the US, to estimate associations of neighborhood- and individual-level SES with individual-level estimates of air pollution concentrations. We used state-of-the art spatial modeling approaches and investigated heterogeneity across regions. MESA has collected data on an array of individual and neighborhood social factors. In addition, the study has generated individual-level space- and time- resolved estimates of airborne concentrations of particulate matter <2.5 μm in aerodynamic diameter ($PM_{2.5}$) and oxides of nitrogen (NO_x). Our study hypotheses were that higher individual and neighborhood SES, measured by income, wealth, education, and occupation, will be associated with lower levels of individual air pollution concentrations; and that measures of neighborhood SES will be more strongly associated with individual-level air pollution concentrations than measures of individual SES.

Methods

MESA is a longitudinal epidemiologic study designed to investigate the progression of subclinical and clinical cardiovascular disease among adults without pre-existing cardiovascular disease (Bild et al. 2002). The cohort is composed of 6,814 white, African-American, Hispanic, and Chinese men and women aged 45 to 84 years recruited in six communities (Baltimore, MD, Chicago, IL, Forsyth County, NC, Los Angeles, CA, New York, New York and St. Paul, MN). The baseline examinations began in July 2000 and ended August 2002; four additional exams were conducted from 2002 until 2012. Institutional review board approval was granted at each study site, and all participants provided written informed consent. For this cross-sectional study, we included MESA participants enrolled at baseline who had complete data on $PM_{2.5}$ or NO_x (the outcomes), SES characteristics (the exposures), and relevant covariates. Two MESA ancillary studies, MESA Air and the MESA neighborhood study, contributed data to this work.

Air Pollution

MESA Air generated predictions of long-term ambient concentrations of $PM_{2.5}$ (in $\mu g/m^3$) and NO_x (in ppb) for each study participant's home address at baseline (Kaufman et al. 2012), as described elsewhere (Sampson et al. 2009; Szpiro et al. 2010). To derive these predictions, data from several sources were used: regulatory monitoring stations from the US Environmental Protection Agency's (EPA) Air Quality System (AQS), monitors deployed by MESA Air at fixed sites throughout the study area, monitors at participant's homes, and monitors placed at specific locations to capture roadway concentration gradients (especially in the NO_x models) (Cohen et al. 2009). In addition, both $PM_{2.5}$ and NO_x models included geographic covariates such as roadway density and land use characteristics, and outputs from dispersion models, to improve predictions. Land use covariates include population density and features such as urban land (defined as land used for residential, commercial, industrial, or transportation purposes), agricultural land, forests, and bodies of water.

The NO_x and $PM_{2.5}$ estimates used in this study reflect estimated average concentrations from January 1 – December 30, 2000 at each participant's home address at baseline. Since predicted NO_x values varied widely among participants (from 8.6 ppb to 173.2 ppb), we used natural log-transformed NO_x values as the outcome in regression models to prevent model nonconvergence. Parameter estimates for NO_x models were exponentiated and are presented as percentage differences from the geometric mean concentration of NO_x. $PM_{2.5}$ concentrations were modeled without transformation, and associations are presented as differences from the mean $PM_{2.5}$ concentration in $\mu g/m^3$. We also performed a sensitivity analysis of associations with $PM_{2.5}$ using annual average $PM_{2.5}$ concentrations measured at the AQS monitor nearest to the participant's home address at baseline as the dependent variable.

Socioeconomic status

We used SES variables from different domains (income, wealth, education and occupation) to capture a broad conceptualization of SES, in contrast with many previous studies that have focused on only one SES domain (Evans and Kantrowitz 2002).

Individual SES: Most individual level SES data were collected from the baseline questionnaire. We examined income, wealth, education, and occupation as well as 2 additional variables (income-wealth index and working outside the home) described in the Supplemental Material, Methods. Total annual family income was classified based on a single question with the following 13 categorical response options: (1) less than $5,000, (2) $5000 - $7,999, (3) $8000 - $11,999, (4) $12,000 - $15,999, (5) $16,000 - $19,999, (6) $20,000 - $24,999, (7) $25,000 - $29,999, (8) $30,000 - $34,999, (9) $35,000 - $39,999, (10) $40,000 - $49,999, (11) $50,000 - $74,999, (12) $75,000 - $99,999 and (13) greater than $100,000. A wealth index specified as a 5 point scale (0 being the lowest level of wealth and 4 the highest) was derived based on family ownership of four assets: homes, vehicles, land, and investments, as described previously (Hajat et al. 2010). Education was classified based on a question with the following 9 categorical response options: (0) no schooling, (1) grades 1-8, (2) grades 9-11, (3) completed high school/GED, (4) some college but no degree, (5) technical school certificate, (6) associate degree, (7) bachelor's degree, (8) graduate or professional school. Occupational information was classified according to five occupational codes from the Bureau of Labor Statistics' standard occupational categories (management/professional; service; sales/office; construction, extraction and maintenance, and production; transportation and material moving.) Less than 0.2% of participants were in farming, fishing, or forestry occupations, so these participants were included in the construction, extraction and maintenance category. Participants who were currently not working were asked to provide information on their main occupation before they stopped working. Those who had never worked outside the home and those who did not provide occupational information were excluded from the occupational classification variable. Occupation categories were collapsed into a dichotomous variable indicating management/professional occupation versus all others. The shapes of the SES-air pollution curves for family income, wealth index, and individual education were evaluated using categorical analyses and were found to be generally linear (data not shown) (Maclure and Greenland 1992). Therefore, using the 13 income categories, the 9 education categories and the 5 wealth categories), we transformed the ordinal variables to z-scores, and modeled the z-scores as continuous variables, to facilitate comparisons with neighborhood SES variables. It should be noted, however, that the z-scores for individual SES variables are based on the original ordinal variables whereas the z-scores for neighborhood SES are based on continuous variables.

Neighborhood SES (NSES): NSES metrics were obtained through the MESA Neighborhoods study. Each participant was assigned to a census tract based on their home address at baseline, and NSES-relevant domains for each census tract were characterized using 11 variables selected *a priori* from the 2000 Census (Census 2002). Income-related variables included median household income, the percent of households living under the poverty level, the percent receiving public assistance, and the percent of single parent families. Wealth-related variables were the percent of households that own their home; the percent that receive interest, dividend, or rental income; and the median value of owner occupied homes. Education was characterized as the percent of persons with at least a high school degree and the percent with at least a Bachelor's degree, and the employment/occupation variables were the percent unemployed and the percent with a non-managerial occupation.

In addition to individual NSES variables we used principal components analysis (PCA) with orthogonal rotation to develop a summary index to represent NSES more generally. Sixteen Census variables were selected to be included in the PCA (see Supplemental Material, Methods for a complete list). Factor based scales included variables that had a factor loading of 0.6 or greater on each factor, standardized the relevant variables and summed them together. Based on the results of the PCA, the following 6 variables were included in the summary index: median household income, percent with household income less than $50,000, median value of owner occupied homes, percent with at least a high school degree, percent with at least a Bachelor's degree and percent with managerial/professional occupations which accounts for about 50% of the overall variability in the original 16 variables. All NSES variables were transformed into z-scores. For ease of interpretation, all SES variables were scaled so that higher values indicate higher SES.

Although we evaluated a total of 11 NSES variables, we report associations of air pollution with only six neighborhood level characteristics here. These variables were selected to represent each of the main SES domains (wealth, income, education and occupation). Specifically, for NSES, we selected median home value because econometric research has used home values to measure the willingness to pay for clean air (Chay and Greenstone 2005; Smith and Huang 1995).

Percent living in poverty, median household income, and percent with at least a high school degree are commonly used in the literature. Percent with a non-managerial occupation potentially has implications for occupational exposure to air pollution, and, finally, the NSES index combines several important NSES variables. The variables not presented were redundant in terms of SES domain; results for these omitted variables were similar in magnitude and precision to the ones presented (data not shown).

Covariates

Participant age, race/ethnicity, gender, and metropolitan area were included as covariates. Models adjusted for these covariates can better inform planned epidemiological analyses, as age, race/ethnicity, and gender are almost always differentially associated with health outcomes.

Models adjusted for population density and high-density land use are also presented as these variables may be associated with SES (via residential segregation) and are also predictors of air pollution. Population density was calculated as the population of the census tract divided by area of the tract not including bodies of water. Land use data were obtained from the Multi-Resolution Land Characteristics Consortium and are based on satellite data from the year 2006. We used a variable representing medium and high density land use (defined as impervious surfaces $\geq$ 50% of the total land cover) within a 100 meter buffer of the participant's address.

Statistical analysis

Analyses were performed using SAS 9.3 (the SAS Institute Inc., Cary, NC) and R version 2.14.0 (The R Project). The bivariate association between air pollution and SES was examined using t-tests and ANOVA, and the shape of the crude air pollution-SES association was examined using

LOESS curves. We used a spatial intrinsic conditional autoregressive (ICAR) model for multivariable analysis. Our model took the following form:

$$y_{ij} = \alpha + \beta SES_i + U_j + V_{ij} \qquad [1]$$

where i indicates the individual, j the census tract, U_j is the spatial random effect at the census tract level, V is the non-spatial random effect for individuals within census tracts, and y_{ij} is the concentration of $PM_{2.5}$ or NO_x estimated at the baseline home address of individual i in census tract j. Through the U_j term, the model assumes that neighboring census tracts (i.e., tracts that share a boundary) are more similar to each other than non-neighboring tracts, and that individuals within census tracts are more similar to each other than individuals living in different census tracts. To identify neighboring census tracts we created shape files (in Arc GIS) of the census tracts where MESA participants resided, and converted the shape files into adjacency graphs in R to identify all census tracts which share a border. Census tracts without neighbors were treated as independent in the model. ICAR models use a Bayesian framework, thus prior specifications were given for the conditional and marginal variance. Several priors were tested to ensure models were robust to changes in prior specification (see Supplemental Material, Methods for more detail). Models were run with the INLA package in R (Rue et al. 2009).

Other modeling approaches were undertaken in order to compare our results to past research. Specifically, we used multilevel model with a random intercept to account for the clustering of individuals within census tracts (see Supplemental Material, Methods for more detail). Lastly, we conducted city specific analyzes in order to explore heterogeneity in associations across MESA sites.

Estimates from multivariable models adjusted only for metropolitan area, a strong confounder of the air pollution – SES association, and full models also adjusted for age, race/ethnicity, sex, metropolitan area, population density and land use are provided here. The Supplemental Material, Table S1 provides additional models including crude models and those adjusted only for age, race/ethnicity, sex and metropolitan area. The alpha level to define statistical significance was set to 0.05 and we conducted complete case analysis.

Results

MESA participants who did not consent to participate in the MESA Neighborhood study (n=623), or who reported baseline addresses outside of one of the six MESA metropolitan areas (n = 11) were not included in the present analysis. In addition, 40 participants did not have $PM_{2.5}$ and an additional 36 did not have NO_x predictions leaving a maximum of 6,140 participants for the $PM_{2.5}$ analysis and 6,104 participants for the NO_x analysis. Up to 224 participants were missing family income data, up to 350 were missing occupation and up to 19 were missing data for education, employment outside the home and the wealth index.

As shown in Table 1, participants were 52% women among 4 race/ethnicities (39% non-Hispanic white, 27% African American, 22% Hispanic and 12% Chinese American) with a mean age of 61.9 years (standard deviation = 10.1) and a relatively even distribution across metropolitan areas with Los Angeles and Chicago having slightly more participants (19% and 17% respectively) than the other 4 sites (16%). In terms of individual SES, over 50% of participants made at least $40,000 per year, 55% had at least 3 points on the wealth index, 37% had at least a college degree and 45% held a management occupation. The mean $PM_{2.5}$ level across the MESA study regions was 17.2 $\mu g/m^3$ (interquartile range (IQR) 3.4 $\mu g/m^3$); the mean NO_x level was

49.8 parts per billion (ppb) (IQR 40.3 ppb). As expected, for the overall study population, individuals with low SES (defined by income, wealth, education, employment and occupation) had higher mean levels of both $PM_{2.5}$ and NO_x than participants with higher SES.

Figure 1 shows a map of each metropolitan area marking participant's home locations (jittered to protect participant confidentiality). As is evident from the maps participants were not uniformly distributed throughout the metropolitan areas included in the study.

There were negative associations of both of the air pollutants with the individual-level SES variables in the metropolitan area adjusted model (model 1) and the fully adjusted model (model 2) shown in Table 2, as well as the crude and minimally adjusted model shown in Supplemental Material, Table S1. Point estimates from the fully adjusted models were attenuated compared to the metropolitan area adjusted models for the association between both pollutants and individual SES variables. For example, after adjusting for all covariates a one unit increase in the z-score for family income (corresponding to a 1-SD unit increase in the ordinal income variable) was associated with 0.03 $\mu g/m^3$ lower $PM_{2.5}$ (95% CI: -0.05, -0.01) and 0.93% lower NO_x (95% CI:-1.33, -0.53). Associations with the wealth index and education were similar. Persons in a management occupation had 0.06 $\mu g/m^3$ lower $PM_{2.5}$, concentrations (95% CI: -0.09, -0.02) and 0.80% lower NO_x concentrations (95% CI: -1.45, -0.15) compared to persons in non-management occupations.

In the population as a whole, higher neighborhood SES metrics were associated with lower concentrations of pollutants. A 1-SD increase in the percentage of persons with at least a high school degree was associated with 0.47 $\mu g/m^3$ lower $PM_{2.5}$ (95% CI: -0.55, -0.40) and 9.61% lower NO_x (95% CI: -10.85, -8.37) after covariate adjustment. Similarly, a 1-SD increase in the

NSES index was associated with 0.30 μg/m^3 lower $PM_{2.5}$ (95% CI: -0.38, -0.23) and 8.72% lower NO_x (95% CI: -9.94, -7.50). In contrast, median home values were not associated with $PM_{2.5}$ (0.004 μg/m^3 difference from the mean with a 1-SD increase in median home values; 95% CI: -0.05, 0.06). The association between NO_x and median home values was substantially smaller than associations with 1-SD increases in other NSES variables and this point estimate was not attenuated with the addition of the other covariates (-3.03% for fully adjusted model and -2.86% for metropolitan are adjusted model respectively). The associations between NSES characteristics and air pollutants in the crude and minimally adjusted models (Supplemental Material, Table S1) are similar to those reported here. In general, 1-SD increases in NSES variables were more strongly associated with both $PM_{2.5}$ and NO_x than corresponding increases in z-scores for individual-level SES factors.

Table 3 provides estimates from fully adjusted models that included both individual and NSES variables simultaneously. We used the NSES index to represent NSES, and family income, wealth index, and individual education as measures of individual SES (Spearman correlation coefficients for the NSES index and the three individual SES variables range from 0.34 to 0.43). A 1-SD increase in the NSES index was associated with 0.29 μg/m^3 lower $PM_{2.5}$ (95% CI: -0.37, -0.22) when controlling for family income, wealth index, and education (model d), essentially unchanged from the estimated association without adjustment for individual-level SES. The individual level SES variables were not statistically significant in model d, but still showed a negative association with $PM_{2.5}$. NO_x was also negatively associated with NSES (-8.43%; 95% CI: -9.65, -7.21), family income (-0.38%; 95% CI: -0.83, 0.07), wealth index (-0.51%; 95% CI: -0.97, -0.06), and individual education (-0.47%; 95% CI: -0.87, -0.08) (model d).

Results from multi-level models for $PM_{2.5}$ and NO_x were very similar to those for the ICAR models; for several variables both the parameter estimates and 95% CI were almost identical (see Supplemental Material, Table S2).

Metropolitan area specific results

Figure 2 shows considerable heterogeneity across metropolitan areas. Individual level SES measures (family income, wealth index) were not associated with either pollutant in some cities, though negative associations consistent with the results for the population as a whole were estimated for most areas. In Chicago, however, a 1-unit increase in the individual wealth index z-score was positively associated with NO_x (0.44 ppb; 95% CI: 0.20, 0.69), indicating higher average exposures among those with higher individual SES. The association between NO_x and both family income and employment outside the home in Chicago were also positive, but were not statistically significant (0.10 ppb; 95% CI: -0.14, 034 and 0.84 ppb; 95% CI: -0.16, 1.84 respectively). This pattern did not, however, hold for individual education and occupation (results not shown) or for $PM_{2.5}$ in Chicago. As expected, crude models and those adjusted for age, race/ethnicity and sex (see Supplemental Material, Table S3) show a similar but slightly stronger association compared to the fully adjusted models shown in Figure 2.

After controlling for covariates, most cities showed negative associations between the pollutants and NSES with the exception of New York, where both pollutants were positively associated with NSES (Figure 2). For example, a 1-SD increase in median household income was associated with 3.09 ppb higher NO_x (95% CI: 1.80, 4.41) and 0.29 $\mu g/m^3$ higher $PM_{2.5}$ (95% CI: 0.09, 0.50). Consistent with estimates for the population as a whole, city-specific differences in $PM_{2.5}$ and NO_x were greater in association with 1-SD increases in NSES variables than with 1-

SD increases in the individual-level measures of SES. It should be noted that the z-scores for SES variables are based on means and SD for the overall study and are not metropolitan area specific.

Discussion

We examined cross-sectional associations of individual and neighborhood SES with individual-level estimates of air pollutant concentrations at each participant's residence at baseline. NSES was more strongly associated with air pollutant concentrations than individual SES. In the overall study population, average $PM_{2.5}$ and NO_x concentrations were lower as NSES increased. However, this was not the case in all city-specific analyses. We observed higher air pollutant concentrations in high SES neighborhoods in New York. Not only do these findings highlight the fact that associations of SES with environmental exposures may be context specific, but they also have implications for health analyses. We recommend that researchers interested in estimating associations of pollutants with health, adjusted for SES, should examine the specific associations present in their geographic regions and specific population samples before deciding how best to account for SES in their analyses.

Our findings are consistent with the previous studies of SES and air pollution (Brulle and Pellow 2006). One SD increases in the SES measures evaluated were associated with up to a 0.47 $\mu g/m^3$ lower $PM_{2.5}$ concentration and 4.20 ppb lower NO_x concentration. These estimates represent at most about 4% of the annual National Ambient Air Quality Standards (NAAQS) for $PM_{2.5}$ (12 $\mu g/m^3$) and about 8% of the annual NAAQS for NO_2 (53 ppb). Given the differences across studies it is difficult to make direct comparisons with the literature; however, one study with a comparable range in NSES found similarly sized associations for $PM_{2.5}$ (Brochu et al. 2011).

While associations with NSES were strong, associations between individual SES measures and air pollution were small. In models including both individual and NSES variables, the parameter estimates for 1-SD increases in the individual SES variables were several orders of magnitude smaller than corresponding associations with 1-SD increases in NSES variables. Our results are consistent with the two previous studies that have evaluated this question, finding NSES characteristics are more strongly associated with air pollutants than individual level SES (Cesaroni et al. 2010; Chaix et al. 2006). Regardless, some caution should be exercised in interpreting these results as individual and neighborhood level variables were collected in different ways and from different sources.

Our data suggest that NO_x has a stronger association with SES than $PM_{2.5}$. NO_x levels are highly dependent on proximity to busy roadways which may also coincide with low SES communities. In addition, the within city variability of NO_x was much greater than that of $PM_{2.5}$ further contributing to the larger magnitudes of effect sizes seen for NO_x. It also should be noted that associations were measured on different scales for the two pollutants (untransformed $PM_{2.5}$ and log-transformed NO_x), thus comparisons should be made with caution.

Considerable differences in levels of air pollution and neighborhood characteristics across the six MESA metropolitan areas suggest the need to evaluate both confounding and effect modification by city. In models adjusted for metropolitan area, we found that estimated associations between $PM_{2.5}$ and SES measures were larger than estimates from unadjusted models. This indicates that metropolitan area may negatively confound the SES-air pollution association in the overall study population. This furthermore suggests that in epidemiologic analyses to assess the health effects of air pollution, SES may be more important for within-city contrasts than between-city contrasts.

Considerable differences in the associations between SES and air pollution were also observed in city-specific models. Lower SES was associated with higher pollution in most metropolitan areas, but in New York, neighborhood SES measures were positively associated with $PM_{2.5}$ and NO_x concentrations, suggesting higher exposures with higher SES. To our knowledge, no studies of American cities, counties, or states have observed the pattern seen in New York, while some studies from Europe and Canada did have similar findings (Buzzelli and Jerrett 2007; Cesaroni et al. 2010). We believe these results are not caused by misclassification of air pollutant concentrations because our predictions are in line with those produced by an extensive air monitoring campaign undertaken by the New York City Department of Health (2012). Instead, the lower SES neighborhoods in New York included in our analyses may be somewhat isolated from roads and high density land uses compared to high SES areas, resulting in lower levels of traffic-related air pollution. Alternatively, high SES neighborhoods (e.g. Upper West Side) may have higher than normal concentrations of pollutants resulting from high density land use and proximity to busy roadways.

The definition and operationalization of a “neighborhood” is dependent on both the outcome under study and the mechanism by which the neighborhood effect is thought to operate (Diez Roux 2001; Lovasi et al. 2008). In the case of air pollution, geographically defined areas may be more relevant than social, historical or administrative boundaries given the spatial nature of pollutants. However, our decision to use census tracts to define neighborhoods was, in part, a practical one: confidentiality is less of a concern, more data are available at the tract level, and tracts result in fewer “islands” in the ICAR model. Furthermore, keeping in mind our objective of informing health effects analyses, we evaluated neighborhood SES metrics based on census tract data that would be readily available to other researchers. There is little evidence that block groups or spatially defined areas (e.g. 1 kilometer buffer) better capture the true concept of a neighborhood (Lovasi et al. 2008). In our data, NSES at the census tract level is highly correlated with NSES at the block group level (correlation coefficients are at least 0.72 for all NSES variables). However, one limitation of using census tracts is that they vary considerably in size across metropolitan areas. Winston-Salem has larger and potentially more heterogeneous census tracts than other MESA sites, which suggests that census tracts may be a less meaningful way to define neighborhoods in this metropolitan area than at other study sites.

Many studies on the impact of place on health use standard multi-level models, similarly much past research on SES and environmental exposures relied on the entirely aspatial ordinary least squares approach (Bowen 2002). One of this study's strengths is that spatial regression approaches were employed and compared to aspatial multi-level models (see Supplemental Material Table S2). In our specific application, aspatial models seem to perform as well as their more complex spatial counterparts, however other studies have not found this to be true (Chaix et al. 2005a; Chaix et al. 2005b; Takagi et al. 2012). Aspatial multilevel models do not consider the correlation of outcomes between areas, only within areas (Auchincloss et al. 2012). This unaccounted spatial autocorrelation may result in incorrect inference (Chaix et al. 2005a; Chaix et al. 2005b). Our use of the spatial ICAR model overcomes this problem.

One methodological concern related to the use of ICAR models was that some census tracts that contained MESA participants had no neighbors, effectively creating "islands". Although the ICAR models can handle this anomaly, more robust estimation would be possible with more contiguous spatial distribution of participants. In addition, recent work suggests that the way the ICAR model allows for spatial random effects may bias the fixed effects (Hodges and Reich 2010); however, this is not a concern in our study because the results from the ICAR and multilevel models were similar. One issue statistical models cannot overcome is the spatial misalignment between the individual-level air pollution outcome and the neighborhood-level SES indicators. This has the potential to impact inference in our study. For example, the effects of living in disadvantaged neighborhoods may not increase concentrations of pollutants which study participants are exposed to as much as our NSES parameter estimates suggest. However, both the NSES variables and the pollutants are defined at and represent each participant's residential location, which should help reduce the impact of spatial misalignment.

The associations presented in this study are not between SES and directly measured $PM_{2.5}$ or NO_x but instead represent associations between SES and estimated air pollution concentrations that are predicted in part based on the covariates used to predict $PM_{2.5}$ and NO_x. Much of the recent research on SES and air pollution uses predicted levels of air pollution to assess the association with social factors (Brochu et al. 2011; Buzzelli and Jerrett 2007; Chaix et al. 2006; Marshall 2008; Molitor et al. 2011; Yanosky et al. 2008). Such prediction models have several benefits, such as leveraging multiple existing data sources, which produce more accurate predictions thus reducing measurement error. In addition, we believe the predicted values are accurate estimates of $PM_{2.5}$ and NO_x concentrations. To corroborate these results, we conducted a sensitivity analysis using nearest monitor data for $PM_{2.5}$ and found similar, albeit attenuated, results (see Supplemental Material, Table S4). Furthermore, our models controlled for some of the same covariates that were in the air pollution prediction models, such as population density and land use, and still observed an association between air pollution and SES, indicating that SES is independently associated with a latent construct of air pollution.

Our study has implications for research on the health effects of air pollution. Differential exposures to air pollution, especially if extended over long periods, could have important implications for population health and health disparities. Although the associations we observed between neighborhood SES and air pollution were generally of small magnitude, they could confound associations of air pollution with health outcomes if the outcomes are associated with SES through mechanisms that do not involve air pollution as an intermediate. These confounding effects may be particularly important when the magnitude of associations of air pollution exposures with health outcomes is also expected to be small. Our results, therefore, suggest that studies of air pollution and health should consider adjustment for SES, especially neighborhood SES. However they also highlight the importance of investigating the SES–air pollution associations in specific settings, as some heterogeneity of associations is to be expected. In fact these results may not be generalizable to the US population as a whole, or even to the larger metropolitan areas represented in the study since participants were not evenly distributed throughout each MESA city.

SES is a powerful force that shapes exposure to a host of biomedical, environmental, and psychosocial factors that influence health (Link and Phelan 1995). Our results highlight how SES is associated with environmental exposures. In the specific case of air pollution exposures, those with higher SES can choose to live in homes further from the highway or leverage community resources to make improvements to air quality. We found that neighborhood SES was an especially important predictor of air pollution exposures. Investigating the drivers of these associations, while important, is beyond the scope of this paper. A more comprehensive discussion of this issue can be found in Mohai et al. (2009). It should be noted that research aimed at understanding the joint effects of air pollution and socioeconomic/ psychosocial factors on health outcomes has the potential to integrate previously disparate fields of study (i.e. social and environmental epidemiology) (Clougherty and Kubzansky 2009; Morello-Frosch and

Shenassa 2006), incorporate health into EJ research (Brulle and Pellow 2006) and produce a more comprehensive examination of environmental factors.

Our study investigated the environmental burden of air pollution and found that overall as neighborhood SES decreased concentrations of air pollutants increased. Furthermore, the air pollution-SES association differed across metropolitan area, specifically for New York City where we observed a positive association between pollutant concentrations and SES. Our results have implications for the confounding effects of SES in studies of air pollution and health and for understanding the possible contributions of air pollution to health disparities.

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Table 1. Mean $PM_{2.5}$ ($\mu g/m^3$) and NO_x (ppb) concentrations by population characteristics

Population characteristic	Total population[a] (%)	Mean $PM_{2.5}$ ($\mu g/m^3$)	p-value[a]	Sample size[b]	Mean NO_x (ppb)	p-value[a]	Sample size[b]
Sex							
Female	52	17.3	0.20	6140	50.5	0.03	6104
Male	48	17.2			49.1		
Race/ethnicity							
non-Hispanic white	39	15.8	<.0001	6140	38.7	<.0001	6104
non-Hispanic black	27	17.2			49.3		
Hispanic	22	18.4			65.4		
Asian	12	19.9			60.1		
Age							
45-54 years	29	17.0	<.0001	6140	48.8	0.0005	6104
55-64 years	28	17.1			48.9		
65-74 years	29	17.4			50.5		
75-84 years	13	17.6			52.8		
Metropolitan Area							
Forsyth County, NC	16	16.6	<.0001	6140	24.4	<.0001	6104
New York, NY	16	18.3			82.6		
Baltimore, MD	16	16.1			42.8		
St. Paul, MN	16	12.8			26.5		
Chicago, IL	17	16.3			45.1		
Los Angeles, CA	19	22.3			72.4		
Family income [c]							
< $12,000	11	18.5	<.0001	5916	62.0	<.0001	5882
$12,000 - < $25,000	19	18.4			57.9		
$25,000 - <$40,000	19	17.4			53.3		
$40,000 - <$75,000	27	16.5			44.7		
≥$75,000	24	16.5			42.5		
Wealth Index							
0 points (low)	10	19.1	<.0001	6139	74.2	<.0001	6103
1	15	18.5			63.6		
2	20	17.8			54.8		
3	33	16.2			39.7		
4 points (high)	22	16.5			39.6		
Education [c]							
≤ high school	35	18.0	<.0001	6122	57.1	<.0001	6087
Some college	28	16.9			47.4		
≥ college degree	37	16.7			44.9		
Occupation [d]							
Non-management occupation	55	17.4	<.0001	5790	52.7	<.0001	5760
Management occupation	45	16.8			45.4		

[a] Denominator for percentage calculations is 6,180. This is the number of participants prior to exclusions for missing $PM_{2.5}$ and NO_x. [b] P-values derived from ANOVA or t-test. [c] Sample size varies because of missing responses.[c] Categories of family income and education presented here have been aggregated for descriptive purposes only. [d] Participants who had never worked outside the home were excluded from the occupational classification variable (n=269); participants who were currently not working were asked to provide information on their main occupation before they stopped working.

Table 2: Differences from mean $PM_{2.5}$ and percent difference from geometric mean of NO_x associated with an increase in individual and neighborhood socioeconomic status (SES) characteristics estimated from intrinsic conditional autoregressive (ICAR) models [a]

SES variable	SD	Model 1 [b]	Model 2 [c]
Difference from mean $PM_{2.5}$ ($\mu g/m^3$) (95% CI)			
Individual SES -			
Family income [d]	3.5	-0.06 (-0.07, -0.04)	-0.03 (-0.05, -0.01) -
Wealth index [d]	1.3	-0.06 (-0.08, -0.04)	-0.03 (-0.05, -0.01) -
Education [d]	2.4	-0.05 (-0.07, -0.03)	-0.03 (-0.05, -0.01) -
Management occupation [e]	NA	-0.07 (-0.11, -0.04)	-0.06 (-0.09, -0.02) -
Neighborhood SES [f]			
Median value of owner occupied homes ($)	204,345	0.01 (-0.04, 0.07)	0.004 (-0.05, 0.06) -
% not in poverty	11.4	-0.35 (-0.41, -0.28)	-0.24 (-0.3, -0.17) -
Median household income ($)	20,469	-0.34 (-0.41, -0.27)	-0.25 (-0.31, -0.18) -
% ≥ high school degree	16.7	-0.60 (-0.68, -0.53)	-0.47 (-0.55, -0.40) -
% management occupations	17.9	-0.50 (-0.57, -0.42)	-0.38 (-0.45, -0.30) -
NSES index	6.3	-0.40 (-0.47, -0.32)	-0.30 (-0.38, -0.23) -
% difference from geometric mean NO_x (95% CI)			
Individual SES -			
Family income [d]	3.5	-1.40 (-1.78, -1.02)	-0.93 (-1.33, -0.53) -
Wealth index [d]	1.3	-1.58 (-1.99, -1.18)	-0.93 (-1.34, -0.53) -
Education [d]	2.4	-1.32 (-1.69, -0.95)	-0.88 (-1.26, -0.50) -
Management occupation [e]	NA	-1.25 (-1.92, -0.58)	-0.80 (-1.45, -0.15) -
Neighborhood SES [f]			
Median value of owner occupied homes ($)	204,345	-2.86 (-3.96, -1.76)	-3.03 (-4.05, -2.02) -
% not in poverty	11.4	-9.36 (-10.58, -8.15)	-6.72 (-7.83, -5.63) -
Median household income ($)	20,469	-10.59 (-11.85, -9.34)	-7.92 (-9.04, -6.81) -
% ≥ high school degree	16.7	-12.91 (-14.28, -11.54)	-9.61 (-10.85, -8.37) -
% management occupations	17.9	-10.57 (-12.05, -9.10)	-7.59 (-8.91, -6.28) -
NSES index	6.3	-11.39 (-12.78, -10.02)	-8.72 (-9.94, -7.50) -

[a] SES variables are scaled so higher values indicate higher SES. [b] Model 1: adjusted for metropolitan - area. [c] Model 2: adjusted for age, race/ethnicity, sex, metropolitan area, population density and high-density land use. -

[d] Parameter estimates for family income, wealth index and education refer to a one unit increase in the z-score for these variables, which were originally ordinal variables that were transformed into z-scores (see - methods section for more details). [e] Management occupation is dichotomous (management versus non-management occupations). [f] Parameter estimates for neighborhood SES variables refer to a one-standard - deviation unit increase in that variable. -

Table 3: Differences from mean $PM_{2.5}$ and percent difference from geometric mean of NO_x associated with one standard deviation unit increase in socioeconomic status (SES) in models including individual and neighborhood SES characteristics simultaneously [a]

	Neighborhood SES index [b]	Family income [c]	Wealth index [c]	Individual education [c]
SD	6.3	3.6	1.3	2.4
$PM_{2.5}$($\mu g/m^3$) (95% CI)				
Model a	-0.3 (-0.37, -0.22)	-0.03 (-0.05, -0.01)	--	--
Model b	-0.3 (-0.37, -0.23)	--	-0.03 (-0.05, -0.01)	--
Model c	-0.3 (-0.37, -0.22)	--	--	-0.03 (-0.05, -0.01)
Model d	-0.29 (-0.37, -0.22)	-0.02 (-0.04, 0.01)	-0.02 (-0.04, 0.01)	-0.02 (-0.04, 0.003)
% change in NO_x (95% CI)				
Model a	-8.54 (-9.77, -7.32)	-0.76 (-1.15, -0.36)	--	--
Model b	-8.59 (-9.82, -7.37)	--	-0.81 (-1.22, -0.41)	--
Model c	-8.53 (-9.76, -7.31)	--	--	-0.70 (-1.08, -0.33)
Model d	-8.43 (-9.65, -7.21)	-0.38 (-0.83, 0.07)	-0.51 (-0.97, -0.06)	-0.47 (-0.87, -0.08)

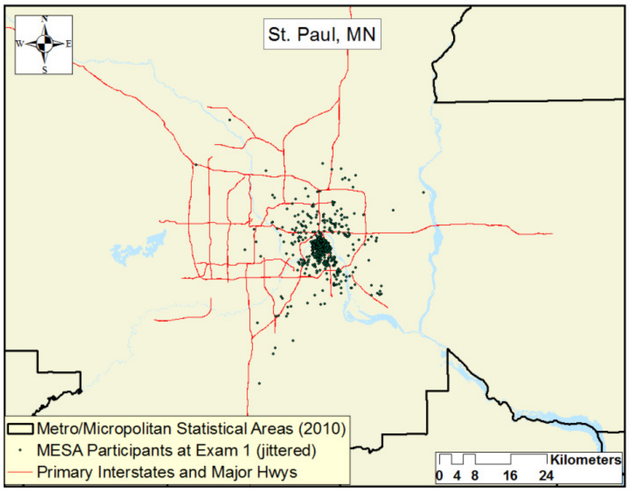
[a] SES variables are scaled so higher values indicate higher SES. Models adjusted for age, race/ethnicity, sex, metropolitan area, population density and high-density land use. [b] Parameter estimates for neighborhood SES index refer to a one-standard deviation unit increase in that variable. [c] Parameter estimates for family income, wealth index and education refer to a one unit increase in the z-score for these variables, which were originally ordinal variables that were transformed into z-scores (see methods section for more details).

-- Variable not included in the model

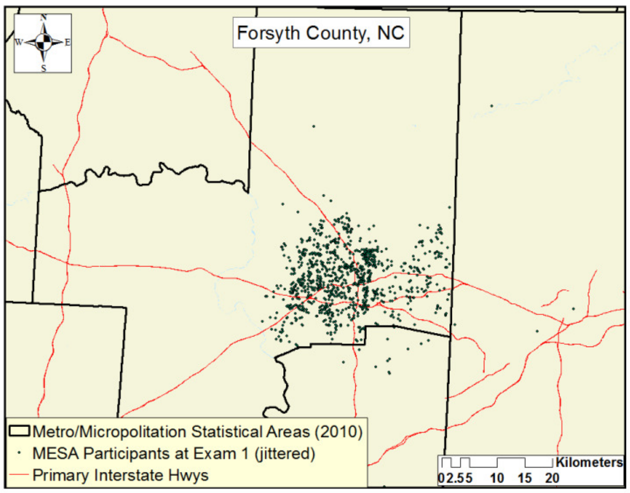
Figure Legends

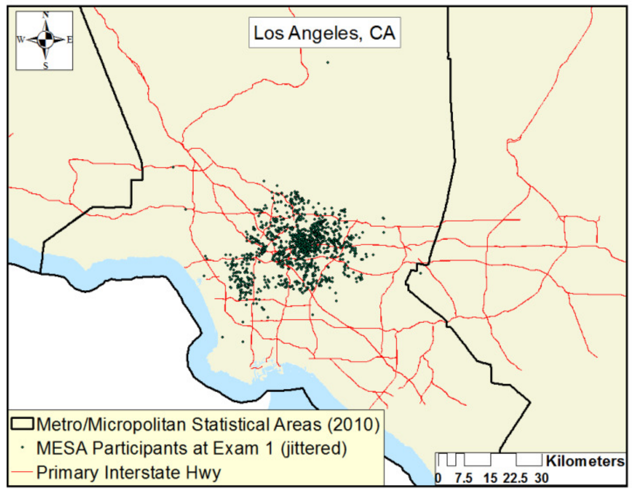
Figure 1: Maps of participant home locations at baseline in each metropolitan area. Locations were jittered to protect participant confidentiality.

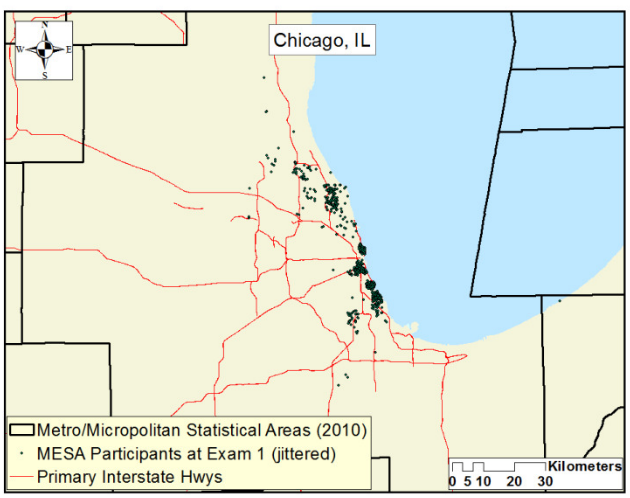
Figure 2: Mean differences in $PM_{2.5}$ ($\mu g/m^3$) and NO_x (ppb) concentrations (95% CI) associated with a one standard deviation unit increase in socioeconomic status (SES) by metropolitan area. SES variables are scaled so higher values indicate higher SES. Models adjusted for age, race/ethnicity, sex, metropolitan area, population density and high-density land use. Parameter estimates for family income and wealth index refer to a one unit increase in the z-score for these variables, which were originally ordinal variables that were transformed into z-scores (see methods section for more details). Parameter estimates for neighborhood SES index refer to a one-standard deviation unit increase in that variable.

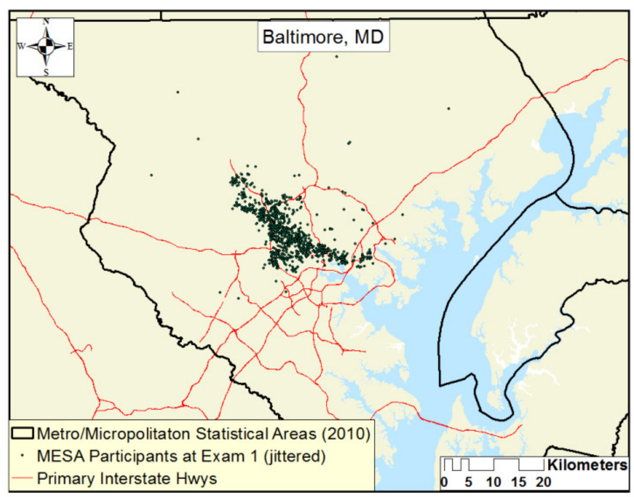

St. Paul, MN
Metro/Micropolitan Statistical Areas (2010)
MESA Participants at Exam 1 (jittered)
Primary Interstates and Major Hwys
0 4 8 16 24
Kilometers

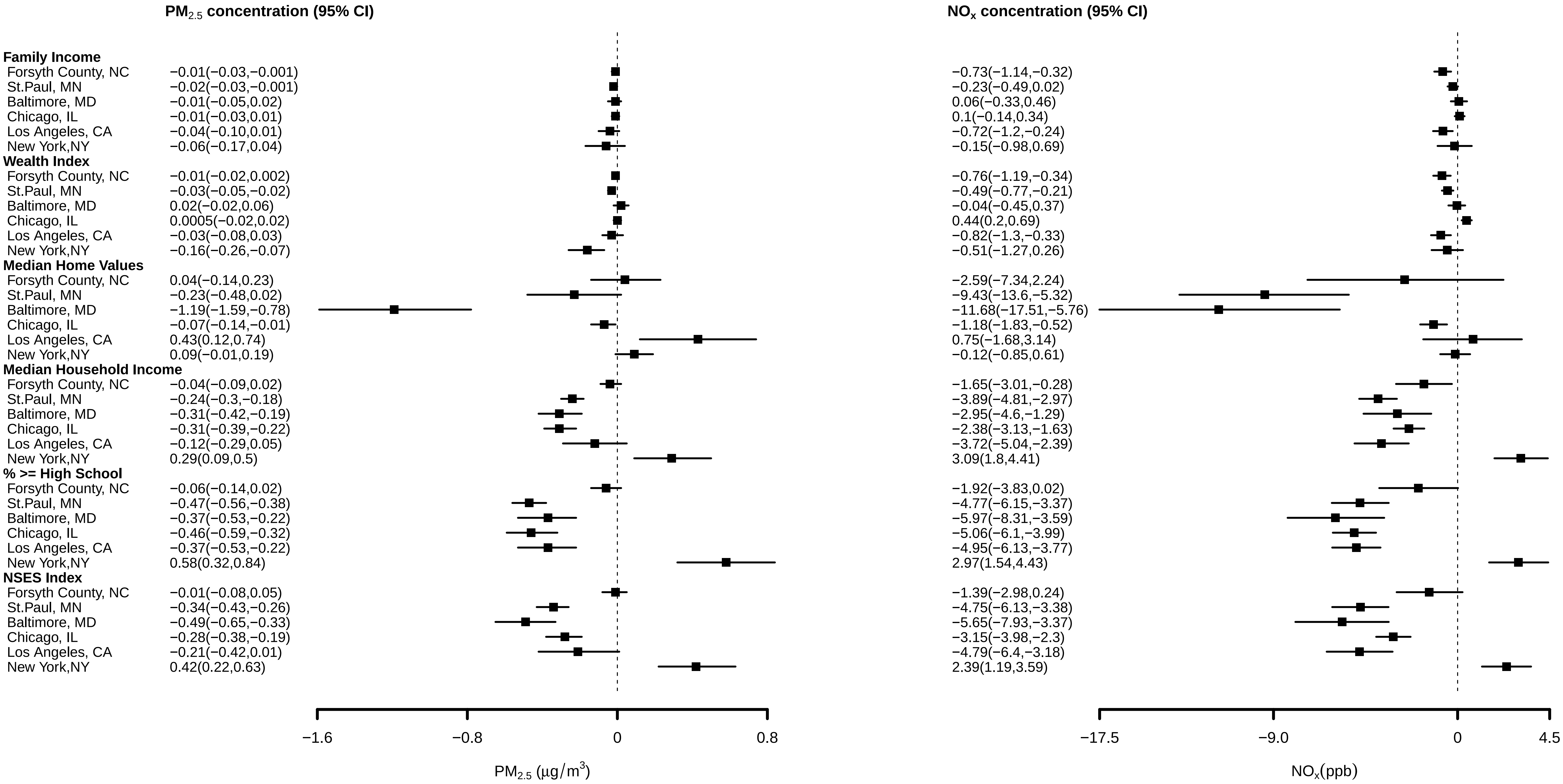

New York, NY
New York City Boroughs
MESA Participants at Exam 1 (jittered)
Primary Interstate Hwy
0 2.5 5 7.5 10
Kilometers


Forsyth County, NC
Metro/Micropolitation Statistical Areas (2010)
MESA Participants at Exam 1 (jittered)
Primary Interstate Hwys
0 2.5 5 10 15 20
Kilometers


Los Angeles, CA
Metro/Micropolitan Statistical Areas (2010)
MESA Participants at Exam 1 (jittered)
Primary Interstate Hwy
0 7.5 15 22.5 30
Kilometers


Chicago, IL
Metro/Micropolitan Statistical Areas (2010)
MESA Participants at Exam 1 (jittered)
Primary Interstate Hwys
0 5 10 20 30
Kilometers


Baltimore, MD
Metro/Micropolitaton Statistical Areas (2010)
MESA Participants at Exam 1 (jittered)
Primary Interstate Hwys
0 5 10 15 20
Kilometers


PM2.5 concentration (95% CI)
NOx concentration (95% CI)
Family Income
Forsyth County, NC −0.01(−0.03,−0.001) −0.73(−1.14,−0.32)
St.Paul, MN −0.02(−0.03,−0.001) −0.23(−0.49,0.02)
Baltimore, MD −0.01(−0.05,0.02) 0.06(−0.33,0.46)
Chicago, IL −0.01(−0.03,0.01) 0.1(−0.14,0.34)
Los Angeles, CA −0.04(−0.10,0.01) −0.72(−1.2,−0.24)
New York,NY −0.06(−0.17,0.04) −0.15(−0.98,0.69)
Wealth Index
Forsyth County, NC −0.01(−0.02,0.002) −0.76(−1.19,−0.34)
St.Paul, MN −0.03(−0.05,−0.02) −0.49(−0.77,−0.21)
Baltimore, MD 0.02(−0.02,0.06) −0.04(−0.45,0.37)
Chicago, IL 0.0005(−0.02,0.02) 0.44(0.2,0.69)
Los Angeles, CA −0.03(−0.08,0.03) −0.82(−1.3,−0.33)
New York,NY −0.16(−0.26,−0.07) −0.51(−1.27,0.26)
Median Home Values
Forsyth County, NC 0.04(−0.14,0.23) −2.59(−7.34,2.24)
St.Paul, MN −0.23(−0.48,0.02) −9.43(−13.6,−5.32)
Baltimore, MD −1.19(−1.59,−0.78) −11.68(−17.51,−5.76)
Chicago, IL −0.07(−0.14,−0.01) −1.18(−1.83,−0.52)
Los Angeles, CA 0.43(0.12,0.74) 0.75(−1.68,3.14)
New York,NY 0.09(−0.01,0.19) −0.12(−0.85,0.61)
Median Household Income
Forsyth County, NC −0.04(−0.09,0.02) −1.65(−3.01,−0.28)
St.Paul, MN −0.24(−0.3,−0.18) −3.89(−4.81,−2.97)
Baltimore, MD −0.31(−0.42,−0.19) −2.95(−4.6,−1.29)
Chicago, IL −0.31(−0.39,−0.22) −2.38(−3.13,−1.63)
Los Angeles, CA −0.12(−0.29,0.05) −3.72(−5.04,−2.39)
New York,NY 0.29(0.09,0.5) 3.09(1.8,4.41)
% >= High School
Forsyth County, NC −0.06(−0.14,0.02) −1.92(−3.83,0.02)
St.Paul, MN −0.47(−0.56,−0.38) −4.77(−6.15,−3.37)
Baltimore, MD −0.37(−0.53,−0.22) −5.97(−8.31,−3.59)
Chicago, IL −0.46(−0.59,−0.32) −5.06(−6.1,−3.99)
Los Angeles, CA −0.37(−0.53,−0.22) −4.95(−6.13,−3.77)
New York,NY 0.58(0.32,0.84) 2.97(1.54,4.43)
NSES Index
Forsyth County, NC −0.01(−0.08,0.05) −1.39(−2.98,0.24)
St.Paul, MN −0.34(−0.43,−0.26) −4.75(−6.13,−3.38)
Baltimore, MD −0.49(−0.65,−0.33) −5.65(−7.93,−3.37)
Chicago, IL −0.28(−0.38,−0.19) −3.15(−3.98,−2.3)
Los Angeles, CA −0.21(−0.42,0.01) −4.79(−6.4,−3.18)
New York,NY 0.42(0.22,0.63) 2.39(1.19,3.59)
−1.6
−0.8
0
0.8
PM2.5 (µg/m3)
−17.5
−9.0
0
4.5
NOx(ppb)