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**Running title:** Air Pollution and Violence in Asthma Etiology

**Keywords:** childhood asthma, exposure to violence (ETV), geographic information systems (GIS), intra-urban variability, nitrogen dioxide (NO$_2$), social-environmental synergy, stress

**Abbreviations:**

- CCDS – Checklist of Children’s Distress Symptoms
- COPD – chronic obstructive pulmonary disease
- EBNHC – East Boston Neighborhood Health Center
- ETV – exposure to violence
- GIS – geographic information systems
- HPA-axis – hypothalamic pituitary adrenal axis
- IgE – immunoglobulin-E
- LUR – land use regression
- MHD – Massachusetts Highway Department
- MISSEB – Maternal Infant Smoking Study of East Boston
- NO$_2$ – nitrogen dioxide
- PAHs – polycyclic aromatic hydrocarbons
- SAM – sympathetic-adrenal-medullary
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BACKGROUND: Disproportionate life stress and consequent physiologic alteration (i.e., immune dysregulation) has been proposed as a major pathway linking socioeconomic position, environmental exposures, and health disparities. Asthma, for example, disproportionately impacts lower-income urban communities, where air pollution and social stressors may be elevated.

OBJECTIVES: We aimed to examine the role of exposure to violence (ETV), as a chronic stressor, in altering susceptibility to traffic-related air pollution in asthma etiology.

METHODS: We developed GIS-based models to retrospectively estimate residential exposures to traffic-related pollution for 413 children in a community-based pregnancy cohort, recruited in East Boston, Massachusetts between 1987 and 1993, using monthly NO₂ measurements for 13 sites over 18 years. We merged pollution estimates with questionnaire data on lifetime ETV and examined the effects of both on childhood asthma etiology.

RESULTS: Correcting for potential confounders, we found an elevated risk of asthma with a one standard deviation (4.3 ppb) increase in NO₂ exposure solely among children with above-median ETV [OR = 1.63 (95% CI = 1.14, 2.33)]. Among children always living in the same community, with lesser exposure measurement error, this association was magnified [OR = 2.40 (95% CI = 1.48, 3.88)]. Of multiple exposure periods, year-of-diagnosis NO₂ was most predictive of asthma outcomes.

CONCLUSIONS: We found an association between traffic-related air pollution and asthma solely among urban children exposed to violence. Future studies should consider socially patterned susceptibility, common spatial distributions of social and physical environmental factors, and
potential synergies among these. Prospective assessment of physical and social exposures may help
determine causal pathways and critical exposure periods.
INTRODUCTION

The gradient of socioeconomic position (SEP) on health may be explained, in part, by a combination of increased contaminant exposures and greater susceptibility to their effects. Air pollution, for instance, may be higher near major roadways, power plants, and industrial sites, where property values are lower, and lower-income populations reside (Graves 1988). Increased life stress among lower-SEP populations has also been proposed as a primary pathway through which SEP impacts health (Gee and Payne-Sturges 2004; Morello-Frosch and Shenassa 2006).

Because of this potential spatial covariance across exposures, and because stress and pollution may influence common physiological pathways (i.e., oxidative stress) and health outcomes (i.e., respiratory disease), stronger methods are needed to disentangle their effects and investigate synergies (Gee and Payne-Sturges 2004; O'Neill et al. 2003; Weiss and Bellinger 2006). The environmental justice literature has documented significant disproportionate contaminant exposures in minority and lower-SEP communities (Brulle and Pellow 2006), and the resultant influence on asthma exacerbation patterns (Maantay 2007). However, fewer studies have considered disproportionate susceptibility among lower-SEP populations.

Exposure to violence (ETV) has been conceptualized as a chronic urban stressor, potentially elevated in communities where pollution is higher. Chronic stress effects of episodic violence is grounded in trauma theory (e.g., post-traumatic stress), detailed elsewhere (Wright 2006). Episodic violence, post-traumatic stress (Augustyn et al., 2002, Overstreet and Braun 2000), and hypervigilance (Gordon and Riger 1991), more prevalent in lower-SEP urban communities (Sampson et al. 1997),
may negatively influence health though physiologic alterations, including immune dysregulation, and behavioral pathways. Many urban caregivers, for example, restrict children’s behavior, keeping them indoors due to fear of violence (Levy et al. 2004; Wright et al. 2004), making children more sedentary, increasing indoor exposures, and decreasing spatial autonomy that is important to development (Katz 1991).

Chronic stress has been linked to asthma exacerbations in cross-sectional (Oh et al. 2004) and prospective (Sandberg et al. 2004) population studies. Other evidence suggests a role for stress in the onset of asthma (Wright et al. 2002; Wright et al. 2004). Chronic stress may influence hypothalamic-pituitary-adrenal (HPA)-axis and cortisol dysregulation (Ockenfels et al. 1995; Hellhammer et al. 1997), glucocorticoid resistance (Miller et al. 2002), sympathetic-adrenal-medullary (SAM) activation, catecholamine production (Glaser and Kiecolt-Glaser 2005), immune mediator function, inflammation (Umetsu et al. 2002), and cytokine production (Chen et al. 2003; Wright et al. 2004). Stress and pollution impact some common physiologic systems, facilitating synergistic effects; for example, psychological stress (Epel et al. 2004) and ozone (Fugisawa 2005) both affect oxidative stress pathways.

Few studies have examined the influence of stress on pollution susceptibility, though some findings suggest differential susceptibility by SEP, possibly mediated by life stress (Morello-Frosch and Shenasssa 2006). Time-series studies indicate effect modification of short-term pollution exposures by SEP (Jerrett et al. 2004; Lin et al. 2004; Martins et al. 2004), though others found no significant modification (Zanobetti and Schwartz 2000). Fewer studies have considered long-term exposures,
though some indicate greater associations between long-term air pollution and mortality among lesser-educated adults (Krewski et al. 2000; Hoek et al. 2002).

In urban settings, traffic-related air pollution may be elevated along with ETV, and previous studies have linked traffic-related air pollution to asthma exacerbation and respiratory outcomes. In the U.S. and Europe, children living or attending school near truck routes and highways show increased asthma and allergy symptoms (Brauer et al. 2002), hospitalizations (Edwards et al. 1994; Lin et al. 2002), allergic rhinitis (Duhme et al. 1996), and reduced lung function (Brunekreef et al. 1997). Traffic-related pollutants have also been associated with asthma development (Zmirou et al. 2004; Gordian et al. 2006).

Incorporating traffic-related air pollution into large-scale epidemiological studies requires models linking traffic and ambient concentrations. Traffic-health relationships have been examined using a number of different traffic indicators, with no consensus on which indictors best capture variability in traffic-related pollution or health outcomes in different settings. Prior studies have successfully extrapolated traffic exposures from sampling homes to larger cohorts using predictive land-use regression (LUR) models (Brauer et al. 2002; Brunekreef et al. 1997). LUR shows strong predictive power for intra-urban nitrogen dioxide ($\text{NO}_2$) variability (Hochadel et al. 2006; Sahsuvaroglu and Jerrett 2004), using traffic and land use characteristics (i.e., population density, major sources).

In this study, we explore the hypothesis that a chronic stressor (here, lifetime ETV) predicts stronger associations between traffic-related air pollution exposure and childhood asthma development. We employ data from the Maternal-Infant Smoking Study of East Boston (MISSEB), a community-
based prospective pregnancy cohort examining asthma, respiratory, and cognitive development. Questionnaires were administered detailing violence exposures, both witnessing and victimization, and avoidance behaviors (staying in at night, avoiding certain areas, keeping children indoors). Because the MISSEB did not examine air pollution, we use geographic information systems (GIS) and LUR at the neighborhood scale to retrospectively estimate pollution exposures, using monthly NO₂ data collected over 18 years in the surrounding neighborhoods.

**MATERIALS and METHODS**

Pregnant women were recruited from East Boston Neighborhood Health Center (EBNHC), Boston, Massachusetts between 1987 and 1993, as described elsewhere (Hanrahan et al. 1992). East Boston is a working-class urban neighborhood bisected by major highways and access roads to Logan International Airport (Figure 1). Following 888 live births originally enrolled, caregivers of 417 children completed questionnaires in 1997 detailing the child’s lifetime violence exposure. Loss to follow-up was largely due to families moving out of the neighborhood; those who moved but continued to participate are included. Written informed consent was obtained from participants (mothers) prior to study initiation, in accordance with both Brigham and Women’s Hospital and Beth Israel Deaconess Medical Center Human Subjects Committees.

**Measures**

**Traffic-related pollution exposures**

NO₂ has been shown to be a reliable indicator for traffic-related primary air pollution (Hochadel et al. 2006; Nieuwenhuijsen 2000). We used a long-term spatially-resolved NO₂ dataset, explored
temporal trends in pollution concentrations, compared multiple traffic indicators as predictors of concentrations, and developed retrospective exposure indices.

Passive NO$_2$ samples were collected contemporaneously one week each month from January 1987 through December 2004, using Palmes tubes and analyzed by spectrophotometry. Samples were collected at 28 unobstructed locations, one meter above ground, across the Logan Airport grounds and surrounding communities (Ayres 2006). We used monthly averages for 13 sites within community spaces, geocoded by hand using aerial photography. Geocoding (identifying residential locations on an active map embedded in a GIS system) allowed for the analysis of spatial characteristics of each location. Missing concentrations were imputed using weighted average concentrations for surrounding months at the same site.

To explain variability in NO$_2$, we considered 25 traffic indicators derived from Massachusetts Highway Department (MHD) 1990 data (Table 1) and site characteristics (land use, elevation, proximity to industrial areas, population density) derived from U.S. Census 2000 data and aerial photography.

$$[\text{NO}_2]_{ij} = \beta_{1j} \cdot \text{Year}_j + \beta_2 \cdot (\text{traffic}_i) + \beta_3 \cdot (\text{land use}_i) + e_{ij}$$  \hspace{1cm} [1]

Where Year$_j$ is a categorical indicator for each sampling year $j$ and capturing secular pollution trends; traffic$_i$ is a suite of traffic characteristics for site $i$ (candidate variables listed in Table 1); and land use$_i$ is a suite of candidate site characteristics (listed above).
Candidate variables were selected with $p < 0.05$ in univariate nonparametric associations with NO$_2$. Backwards elimination produced a parsimonious model with $p < 0.1$ for all terms. As the assumption of normal distribution in NO$_2$ could not be rejected (Shapiro-Wilk $p<0.0001$), concentrations were not transformed. Models were run in PROC GLM, corroborated in PROC MIXED with random effects by site, to account for within-site autocorrelation.

**Residential retrospective exposure estimates**

Using the predictive NO$_2$ model, we created residential exposure indices. Each child’s address at enrollment (during pregnancy) and follow-up were geocoded using the ESRI StreetMap Address Locator, and spatial variables derived in GIS, to apply Equation 1 to each address. NO$_2$ exposure estimates were defined for each year of follow-up, for both reported residences. NO$_2$ exposures for years following 1997 were derived using the questionnaire address; between 1990 and 1997, lacking residential information, we created time-weighted annual exposures using the two known addresses. For example, estimated exposure in 1991 for a child enrolled in 1990 is: $[(6/7) \times \text{(estimated NO}_2 \text{ in 1991 at residence reported at enrollment)} + (1/7) \times \text{(estimated NO}_2 \text{ in 1991 for residence reported in 1997)}].$

We created this lifetime NO$_2$ exposure trajectory for each child, and calculated exposures during seven intervals potentially influencing asthma etiology:

1. lifecourse through diagnosis (or end of follow-up)
2. year of birth
3. before age 5 (median age of diagnosis)
4. year of ETV questionnaire (known residential address)
(5) years between first violent event and diagnosis

(6) year of diagnosis

(7) one year prior to diagnosis

For intervals ending at diagnosis, median diagnosis age was used for non-asthmatics. Some exposures following diagnosis (i.e., at ETV questionnaire) are considered due to the measure’s relative stability. Univariate logistic regression for each NO₂ interval against asthma diagnosis was used to select an optimal exposure interval, which is used going forward. Sensitivity analyses on the final epidemiological models assessed whether interval selection affected results.

Violence exposure assessment

Exposure to violence was assessed using the My Child’s ETV scale (Buka 1997; Selner-O'Hagan et al. 1998). At interview, children ranged from four to 11.5 years in age; those over age eight also answered the questionnaire themselves. The questionnaire includes items on witnessing events: (1) hitting, slapping, punching, (2) a shooting, (3) a stabbing, or (4) hearing gunshots. We added one question on witnessing domestic verbal abuse. Respondents indicate the event frequency, over their lifetime and past year, on a scale of 1 (0 – 1 time) to 4 (more than 10 times). Caregivers reported child’s approximate age at first witnessing.

Rasch modeling summarized responses into a continuous score, modeling the conditional probabilities for each “yes” response, given the presumed event severity and each child’s true-but-unobserved exposure (a latent construct) (Kindlon et al. 1996). Expanding on this approach, the model was generalized to account for features theoretically influencing severity: frequency, whether
events occurred at home, whether the child knew the victim(s) or perpetrator(s), and included parent and child’s report, wherever available, as detailed elsewhere (Franco Suglia 2006).

As a validity check, we assessed the relationship between the Rasch ETV and Checklist of Children’s Distress Symptoms (CCDS) (Richters and Martinez 1990), administered contemporaneously. CCDS is a parental report of 24 posttraumatic stress symptoms over the prior six months (e.g., irritability, inability to fall asleep, nightmares, fear of attending school). The lifetime Rasch ETV and six-month CCDS were significantly correlated (Spearman r = 0.21, p < 0.0001), corroborating an association between violence and distress symptoms reported elsewhere (Martinez and Richters 1993).

**Child’s asthma diagnosis**

During MISSEB follow-up, parental reports of child’s asthma diagnosis was ascertained through bimonthly telephone or face-to-face interviews over the child’s first two years, every six months through age four, and annually thereafter. Parents were asked, “Since we last spoke to you, have you been told by a doctor or nurse that your child has asthma?” and likewise for asthmatic bronchitis. The same questions were asked upon ETV questionnaire administration. Children were considered to have asthma if the parent reported any diagnosis of asthma or asthmatic bronchitis.

**Potential confounders**

Demographic characteristics, smoking, and medical history were also ascertained through standardized questionnaires administered during MISSEB follow-up visits. Maternal education was categorized as less than high school, high school graduate or technical school graduate, or some
college. At each clinic visit during pregnancy, mothers were asked about smoking status. A urine specimen was obtained for determination of a creatinine-corrected cotinine level as detail, and mothers were classified as never-smokers during pregnancy if they always reported never smoking and their urine cotinine levels were consistently < 200 ng cotinine/mg creatinine (Hanrahan et al. 1992). Maternal asthma status was based on report of physician diagnosed asthma using the standardized American Thoracic Society (ATS) respiratory questionnaire (Ferris 1978).

**Data Analysis**

We examine independent associations of air pollution and ETV on asthma diagnosis using univariate odds ratios. To examine the modifying effect of violence on the NO$_2$-asthma relationship, we constructed two interaction models, of the forms used elsewhere (Tsaih et al. 2004):

$$\text{logit(哮喘诊断)} = \text{截距} + \beta_1*(I_{\text{LowETV}} \times \text{NO}_2) + \beta_2*(I_{\text{HighETV}}) + \beta_3*(I_{\text{HighETV}} \times \text{NO}_2) + (\text{潜在混杂因素})$$ [2]

where $I_{\text{LowETV}} = 1$ if below-median ETV (reference group), 0 otherwise. $I_{\text{HighETV}}=1$ if above-median ETV, 0 otherwise. NO$_2$ is a centered continuous variable with standard deviation equal to 1.0; odds ratios thus refer to a one standard deviation increase above the mean. Potential confounders included maternal asthma, education, smoking before and after pregnancy, child’s sex and age. Equation 2 produces the slopes by ETV group and their significance.

A second regression model contained main effects for ETV and NO$_2$, and their interaction:

$$\text{logit(哮喘诊断)} = \text{截距} + \beta_1*(I_{\text{HighETV}}) + \beta_2*(\text{NO}_2) + \beta_3*(I_{\text{HighETV}} \times \text{NO}_2)$$
Equation 3 produces the statistical test of the interaction; if $\beta_3$ differs significantly from zero, ETV significantly modifies the association of NO$_2$ on asthma.

Because NO$_2$ data were collected only in East Boston and adjoining Winthrop, we expect NO$_2$ estimates to be more accurate for children always living in these neighborhoods. Likewise, the Rasch ETV likely better reflects chronic stress among children always living in the same community where exposure occurred. Therefore, all statistical analyses are performed for the entire cohort, and repeated using only lifetime residents of East Boston and Winthrop.

RESULTS

We were able to geocode home addresses for 409 children at follow-up, and 369 at enrollment. Demographics of those children and their caregivers are presented in Table 2. Caregivers of 100 children (24%) reported asthma diagnoses during follow-up; caregivers of an additional 7 children (2%) retrospectively reported asthmatic bronchitis. Only 8% of mothers reported ever having asthma. ETV varied significantly; 46% reported at least one event, 18% reported at least two, and Rasch scores ranged from -1.00 to 2.93. Lifetime residents did not significantly differ from the full cohort in ETV, asthma rates, or other demographic factors or confounders.

Traffic-related pollution and LUR models

Over 18 years, 2291 monthly NO$_2$ samples were collected and analyzed, averaging 24.0 ppb (0.78 - 69.4 ppb). Some overall NO$_2$ decline occurred over time, with some re-ordering of sites (Figure 2).
LUR models explained significant variability as a function of secular trends, traffic density within 500 meters, distance from major roads, and block group population density ($R^2 = 0.83$; Table 3). More variability in NO$_2$ was explained by spatial ($R^2 = 0.53$) than temporal terms ($R^2 = 0.29$). Residential estimates averaged 27.5 ppb (18.7 - 42.6 ppb) overall, higher than measured concentrations, as several NO$_2$ samplers were located in open spaces (i.e., parks, backyards), while cohort homes clustered near major roadways (Figure 1).

$NO_2$ and ETV on asthma

Univariate odds ratios for the seven candidate NO$_2$ exposure periods indicated that a one SD increase only in year-of-diagnosis NO$_2$ (4.3 ppb) showed near-significant associations with asthma for the full cohort [OR = 1.17 (95% CI = 0.94, 1.46)], and was used going forward as our key exposure metric.

For the full cohort, we found no independent effect of ETV on asthma [OR = 0.98 (95% CI = 0.78, 1.22)]. Stratified analyses, however, indicated that year-of-diagnosis NO$_2$ was significantly associated with asthma solely among children with above-median ETV [OR = 1.65 (95% CI = 1.16, 2.34)]. For children with below-median ETV, there was no association between NO$_2$ and asthma [OR = 0.94 (95% CI = 0.70, 1.26)].

Among lifetime resident children, with less expected exposure measurement error, we found similar effects with greater magnitude. There was a near-significant effect of NO$_2$ on asthma [OR = 1.28 (95% CI = 0.97, 1.69)], with no independent effect of ETV [OR = 1.12 (95% CI = 0.84, 1.48)]. Stratified analyses indicated that NO$_2$ was significantly associated with asthma solely among
children with above-median ETV [OR = 2.33 (95% CI = 1.47, 3.71), vs. OR = 0.87 (95% CI = 0.59, 1.28) with below-median ETV].

Multivariate logistic regression was used to formally test the observed interaction, adjusting for potential confounders. In stratified analysis across the full cohort, we found elevated odds of asthma with increased NO$_2$ solely among children with above-median ETV (Table 4), and the magnitude was unaffected by addition of potential confounders [adj OR = 1.63 (95% CI = 1.14, 2.33)]. The interaction between NO$_2$ and ETV was statistically significant (p=.03), and robust to inclusion of both main effects.

Among the lifetime residents, in multivariate logistic regression, we found similar associations with greater magnitude. Stratified analyses indicated elevated odds of asthma with increased NO$_2$ solely among children with above-median ETV [adj OR = 2.40 (95% CI = 1.48, 3.88)]. The NO$_2$-ETV interaction term was statistically significant (p = .0009), and robust to inclusion of main effects.

Sensitivity analyses indicated that only average NO$_2$ for the years between first violence exposure and asthma diagnosis could be substituted for year-of-diagnosis NO$_2$ with significance [adj OR = 1.52 (1.05, 2.19)] for children with above-median ETV, in the full cohort multivariate model. We repeated analyses removing 10 children whose diagnosis occurred prior to first violent event, with little bearing on results. Lastly, sensitivity analyses indicated that median-dichotomized My ETV, My Child’s ETV, and CCDS scores could not be substituted for the Rasch indicator with significance.
DISCUSSION

We found an association between traffic-related pollution (NO$_2$) and asthma diagnosis only among children with elevated ETV, after controlling for potential confounders. Of multiple exposure intervals, year-of-diagnosis NO$_2$ best predicted asthma (with some evidence for NO$_2$ after first violence exposure), supporting a theoretical model wherein individuals may become susceptible or ‘primed’ through social pathways to some environmental triggers, including traffic-related pollutants. Despite limitations of our datasets, these results are in agreement with evidence elsewhere that chronic stress may shape biologic response in early life (Wright et al. 2004), and potentiate effects of air pollution through common physiologic systems.

Our findings contribute to the existing environmental justice literature by identifying potential changes in pollution susceptibility within communities affected by violence and other stressors. We also indicate ancillary effects of violence on children in urban communities, in addition to direct injury and post-traumatic stress. Sampson et al. (1997) identify associations among neighborhood deterioration, violence, and low collective efficacy (social control of neighborhoods through residents’ collective effort); we observe that a heightened susceptibility to pollution, associated with violence exposures or fear thereof, may lead to synergistic health effects of social and physical environmental conditions.

Although our findings are biologically plausible and highly suggestive, there are potential limitations in interpreting our models. A clear limitation is our small sample size for investigating multiplicative effects; in spite of the relatively high asthma prevalence (26%), a larger cohort would be required to consider interactions across numerous potential risk factors. The pollution model relies on NO$_2$ data,
commonly used as a marker of primary vehicular emissions, but not necessarily representative of all pollutants of interest. Roadway construction and airplane technology changes made it unclear \textit{a priori} whether NO$_2$ could be predicted by spatial indicators in this neighborhood, particularly using 1990 traffic data, though our model proved robust. We lacked complete residential history, likely creating some misclassification in a cohort with significant residential instability. However, we found no difference in asthma prevalence or exposures between movers and non-movers, thus we expect misclassification to be non-differential, biasing results towards the null, and making our significant results more noteworthy.

The interpretation of our interaction model is complicated by the fact that behaviors may differ in violent neighborhoods, where parents often keep children indoors due to fear of violence. As such, children may be more exposed to indoor NO$_2$, which is generally higher than outdoors, influenced both by infiltration from outdoors and by smoking, gas stoves, and other sources which may be more prevalent in lower-income communities (Baxter et al. 2006; Spengler et al. 1983). Future studies should examine differential susceptibility to a wider range of pollution exposures, including indoor allergens and environmental tobacco smoke; although we accounted for maternal smoking, we did not examine the effect of other smokers in the home. Likewise, ETV may proxy for other social exposures responsible for the susceptibility effect we found; children witnessing violence may have greater family instability (Overstreet and Braun 2000) or may be directly victimized, potentially leading to injury-related susceptibilities.

We aimed to investigate whether a psychosocial stressor modifies pollution effects on asthma, and would prefer a long-term stress measure to corroborate the ETV scale. The CCDS elicits distress
using a six-month symptoms recall, inappropriate to our goal of capturing lifecourse stress. The correlation between CCDS and violence does, however, corroborate an association, supporting the plausibility of stress pathways to pollution susceptibility, and should be investigated further.

Reporting bias, generally under-reporting by survivors, perpetrators, and witnesses, hampers quantitative violence research (Gordon and Riger 1991), particularly for domestic and intimate violence. Our questionnaire focused largely on within-community events, potentially more accurately reported. A prior analysis indicated that parents under-estimate older children’s exposures, but are better corroborated for near-home events, potentially due to shared experience (Thomson et al. 2002). We were unable to examine direct victimization, as very little was reported, owing either to low prevalence or under-reporting, and thus we likely have some misclassification of true ETV. Most asthma cases were reported during longitudinal follow-up, limiting recall bias in diagnoses, but our retrospective violence report is subject to recall bias. To assess recall bias in violence reports, we asked the caregiver to report on asthma episodes triggered by violence; as very few parents associated violent events with asthma symptoms, recall bias in ETV by asthma status is unlikely.

In spite of these limitations, our study provides evidence of a synergistic effect between social and physical factors in asthma etiology. The study also provides a model for retrospectively estimating traffic-related exposures, accounting for intra-community heterogeneity and temporal trends using GIS. We were able to create temporally-calibrated estimates using a spatially dense and temporally rich pollution dataset of NO\textsubscript{2} measurements collected throughout our epidemiologic study period. Though few studies will have access to such data, existing models provide insight about site
characteristics influencing exposure variability, and spatially-resolved satellite pollution data may prove useful in some settings (Liu et al. 2005).

In future studies, a wider and more frequently-assessed suite of social stressors and perceived stress measures should be employed to examine stress trajectories over time and temporality in susceptibility to environmental triggers. The roles of social support and health beliefs in mediating the effects of perceived stress on health outcomes should be considered as buffers in the pathway from stressor to stress response, the latter of which may influence contaminant susceptibility and health (Chen et al. 2003). We observed no correlation between ETV and pollution levels, but suggest longitudinal investigation of multiple exposures, and multiple pathways, are needed to further elucidate these effects. The spatial correlation across multiple exposures deserves greater investigation, and should be addressed in larger studies investigating spatial autocorrelations across, and potential synergies among, social and physical environmental factors.
### Table 1: Traffic indicators explored as predictors of monthly NO₂ concentrations at sampling sites

<table>
<thead>
<tr>
<th>Indicator type</th>
<th>Indicator</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cumulative density scores:</strong></td>
<td>Unweighted traffic density within: 50, 100, 200, 300, 500m buffers</td>
<td>Vehicle-meters per day/m²</td>
</tr>
<tr>
<td></td>
<td>Kernel (inverse-distance)-weighted density: 50, 100, 200, 300, 500m buffers</td>
<td>Vehicle-meters per day/m²</td>
</tr>
<tr>
<td></td>
<td>Density of urban roads ( &gt; 8500 cars/day) within 200m</td>
<td>Vehicle-meters per day/m²</td>
</tr>
<tr>
<td><strong>Summary measures:</strong></td>
<td>Total roadway length within: 50, 100, 200, 300, 500m</td>
<td>Meters</td>
</tr>
<tr>
<td></td>
<td>Total average daily traffic (ADT) * Length (VMT) within 200m</td>
<td>Vehicle-meters per day/m²</td>
</tr>
<tr>
<td><strong>Distance-based measures</strong></td>
<td>Distance to nearest urban road (&gt;8500 cars/day)</td>
<td>Meters</td>
</tr>
<tr>
<td></td>
<td>To nearest major road (&gt;13,000 cars/day)</td>
<td>Meters</td>
</tr>
<tr>
<td></td>
<td>To nearest highway (&gt;19,000 cars/day)</td>
<td>Meters</td>
</tr>
<tr>
<td></td>
<td>To nearest MHD-designated truck route</td>
<td>Meters</td>
</tr>
<tr>
<td><strong>Characteristics of nearest major road:</strong></td>
<td>Average daily traffic (ADT)</td>
<td>Vehicles/day</td>
</tr>
<tr>
<td></td>
<td>ADT/ Distance to major road</td>
<td>(Vehicles/day) / meter</td>
</tr>
<tr>
<td></td>
<td>Diesel fraction</td>
<td>Percent (%)</td>
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<tr>
<td></td>
<td>Trucks per day</td>
<td>Vehicles/day</td>
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<tr>
<td></td>
<td>Trucks/ Distance to major road</td>
<td>(Vehicles/day) / meter</td>
</tr>
</tbody>
</table>
Table 2: Characteristics of cohort participants

<table>
<thead>
<tr>
<th></th>
<th>Full cohort (n = 413)</th>
<th>Lifetime residents (n = 255)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Percent (%)</td>
<td>Percent (%)</td>
</tr>
<tr>
<td><strong>Child characteristics:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (female)</td>
<td>50%</td>
<td>53%</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>52%</td>
<td>52%</td>
</tr>
<tr>
<td>Caucasian</td>
<td>44%</td>
<td>44%</td>
</tr>
<tr>
<td>Asthma diagnosis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>26%</td>
<td>24%</td>
</tr>
<tr>
<td>Low ETV – Low NO₂</td>
<td>24%</td>
<td>22%</td>
</tr>
<tr>
<td>Low ETV – High NO₂</td>
<td>26%</td>
<td>21%</td>
</tr>
<tr>
<td>High ETV – Low NO₂</td>
<td>16%</td>
<td>11%</td>
</tr>
<tr>
<td>High ETV – High NO₂</td>
<td>36%</td>
<td>43%</td>
</tr>
<tr>
<td><strong>Mean (SD)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age in 1997</td>
<td>6.8 (1.6)</td>
<td>6.6 (1.6)</td>
</tr>
<tr>
<td>Rasch ETV</td>
<td>0.60 (0.97)</td>
<td>0.60 (0.96)</td>
</tr>
<tr>
<td>NO₂ Year-of-diagnosis</td>
<td>27.5 (4.3)</td>
<td>27.6 (4.3)</td>
</tr>
<tr>
<td><strong>Maternal characteristics:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asthma diagnosis</td>
<td>7.7%</td>
<td>7.0%</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(less than high school)</td>
<td>41%</td>
<td>43%</td>
</tr>
<tr>
<td>Smoker</td>
<td>25%</td>
<td>22%</td>
</tr>
</tbody>
</table>
Table 3: Land use regression modeling results for annual average NO\textsubscript{2} at 13 sampling sites.

<table>
<thead>
<tr>
<th>Year (categorical)</th>
<th>Estimate (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1987</td>
<td>19.84</td>
</tr>
<tr>
<td>1988</td>
<td>23.06</td>
</tr>
<tr>
<td>1989</td>
<td>24.12</td>
</tr>
<tr>
<td>1990</td>
<td>21.97</td>
</tr>
<tr>
<td>1991</td>
<td>20.62</td>
</tr>
<tr>
<td>1992</td>
<td>19.02</td>
</tr>
<tr>
<td>1993</td>
<td>19.90</td>
</tr>
<tr>
<td>1994</td>
<td>21.29</td>
</tr>
<tr>
<td>1995</td>
<td>18.20</td>
</tr>
<tr>
<td>1996</td>
<td>17.98</td>
</tr>
<tr>
<td>1997</td>
<td>22.65</td>
</tr>
<tr>
<td>1998</td>
<td>24.14</td>
</tr>
<tr>
<td>1999</td>
<td>23.55</td>
</tr>
<tr>
<td>2000</td>
<td>21.45</td>
</tr>
<tr>
<td>2001</td>
<td>21.22</td>
</tr>
<tr>
<td>2002</td>
<td>17.35</td>
</tr>
<tr>
<td>2003</td>
<td>11.85</td>
</tr>
<tr>
<td>2004</td>
<td>10.64</td>
</tr>
</tbody>
</table>

Overall ($R^2 = 0.83$)

- Distance to Major Road ($>13,000$ cars/day) (meters): $-1.27 \times 10^{-3}$ (<.0001)
- Kernel traffic density within 500m (VMT/day): 0.0775 (<.0001)
- Population Density (persons/km\textsuperscript{2}): $1.086 \times 10^{-4}$ (<.0001)
Table 4: Multivariate model for asthma diagnosis. Odds ratios for NO$_2$ are associated with a one standard deviation (4.3 ppb) increase.

<table>
<thead>
<tr>
<th></th>
<th>Full cohort</th>
<th>Lifetime residents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maternal Asthma (ever diagnosed)</td>
<td>1.31 (.58, 2.96)</td>
<td>0.89 (.29, 2.74)</td>
</tr>
<tr>
<td>In-uterо tobacco smoke exposure</td>
<td>1.07 (.44, 2.58)</td>
<td>1.87 (.53, 6.57)</td>
</tr>
<tr>
<td>Maternal smoking since birth</td>
<td>1.10 (.70, 1.72)</td>
<td>0.85 (.45, 1.63)</td>
</tr>
<tr>
<td>Education (less than HS)</td>
<td>1.14 (.71, 1.81)</td>
<td>1.12 (.60, 2.07)</td>
</tr>
<tr>
<td>Child’s Sex (female)</td>
<td>0.85 (.54, 1.34)</td>
<td>0.62 (.34, 1.14)</td>
</tr>
<tr>
<td>Child’s Age (7+ years)</td>
<td>1.44 (.90, 2.33)</td>
<td>1.06 (.56, 2.00)</td>
</tr>
<tr>
<td>High ETV</td>
<td>0.89 (0.56, 1.43)</td>
<td>1.10 (0.59, 2.04)</td>
</tr>
<tr>
<td>NO$_2$ Year of Diagnosis: Low ETV</td>
<td>0.99 (0.73, 1.34)</td>
<td>0.85 (0.56, 1.27)</td>
</tr>
<tr>
<td>NO$_2$ Year of Diagnosis: High ETV</td>
<td>1.63 (1.14, 2.33)</td>
<td>2.40 (1.48, 3.88)</td>
</tr>
</tbody>
</table>
REFERENCES


FIGURE LEGENDS

Figure 1: Distribution of East Boston cohort and NO$_2$ sampling sites. Darker shading indicates higher estimated NO$_2$.

Figure 1A: Residential addresses at enrollment (about 1990).

Figure 1B: Residential addresses at violence questionnaire date (in 1997).

Figure 2: Annual average NO$_2$ (ppb) across 13 neighborhood sampling sites. For legibility, average annual values at three clustered sites on Bayswater Street and in adjacent Winthrop have been combined. Numbers in the legend correspond to sampling sites in Figures 1a and 1b.
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