EXPOSURE ASSESSMENT METHODS FOR EXAMINING THE ROLE OF NON-CHEMICAL STRESSORS IN ENVIRONMENTAL HEALTH DISPARITIES

by

Jessie Loving Carr Shmool

BA, Macalester College, 2001

MPH, Columbia University Mailman School of Public Health, 2010

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This dissertation was presented

by

Jessie Loving Carr Shmool

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and approved by

Dissertation Advisor:

Jane Ellen Clougherty, ScD, MS
Associate Professor, Director of Exposure Science
Department of Environmental and Occupational Health
Graduate School of Public Health, University of Pittsburgh

Committee Chair:

Bruce R. Pitt, PhD
Professor and Chair
Department of Environmental and Occupational Health
Graduate School of Public Health, University of Pittsburgh

Committee Members:

Fernando Holguin, MD, MPH
Assistant Professor of Medicine and Pediatrics
Assistant Director, Asthma Institute
Department of Medicine, Division of Pulmonary, Allergy, and Critical Care Medicine
University of Pittsburgh

Ravi Sharma, PhD
Assistant Professor, Associate Director of Public Health Informatics
Department of Behavioral and Community Health Sciences
Graduate School of Public Health, University of Pittsburgh

Michael A. Yonas, DrPH, MPH
Senior Program Officer, Social Innovation, Research and Special Initiatives
The Pittsburgh Foundation

Jane E. Clougherty, ScD, MS

Bruce Pitt, PhD

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ABSTRACT

Increases in chronic diseases among children are cause for public health concern and action, particularly as children of color and low socioeconomic position are disproportionately impacted, with far-reaching consequences for health and well-being over the life-course. Environmental toxicants and non-chemical stressors have been linked with adverse health outcomes and disparities. Specifically, recent toxicological and epidemiological evidence suggests that chronic psychosocial stress may modify pollution effects on health. Thus, there is increasing interest in refined methods for assessing and incorporating non-chemical exposures, including social stressors, into environmental health research, towards identifying whether and how psychosocial stress interacts with chemical exposures to influence health and health disparities.

The overall objective of this dissertation is to apply exposure science principles to develop and validate methods for non-chemical exposure assessment, toward examining differential susceptibility and disproportionate exposures in social-environmental epidemiology.

To do so, I utilize a spatial approach to characterize intra-urban variation in and correlation among social stressors, socioeconomic position, and air pollution exposures across New York City. I present flexible GIS-based approaches for reformulating aggregate administrative indicators for global correlation analysis, accounting for spatial autocorrelation, and assessing perceived neighborhood geography. I assess multiple foci of the stress process paradigm using qualitative and quantitative methods, and evaluate the extent to which multiple components of social environment are implicated in psychosocial pathways, with specific attention to distinguishing socioeconomic and stress pathways.

Complex interaction between air pollution and area-level deprivation effects on term birth weight suggested differential population susceptibility, and the need for mechanism-specific non-chemical exposure metrics. Spatially, ecologic indicators of social stressor exposures and air pollution were not consistently correlated with each other, or with indicators of socioeconomic position, and were not consistently associated with child asthma exacerbation rates. Community perceptions of important social stressors assessed through a qualitative process informed upon the design and implementation of a systematic survey to validate the resonance of ecologic stressor indicators against individual stress perception and mental health. Overall, these non-chemical exposure assessment methods enable characterization of complex confounding in urban environments, toward refining epidemiologic investigations of separate and combined effects of social and chemical exposures.

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ACKNOWLEDGEMENTS

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I dedicate this work to my husband, Roey, who reminds me that science is a creative endeavor.

1.0 NON-CHEMICAL STRESSORS AND SUSCEPTIBILITY TO ENVIRONMENTAL CHEMICALS

Increases in chronic diseases among children in the United States (US) and globally are cause for public health concern and action. Chronic ill health in youth can dramatically impact upon developmental milestones and educational achievement, and herald adverse health outcomes over the life-course (Perrin et al. 2007). In the US, asthma is the most common chronic disease among children – most recent surveillance data measure current asthma diagnosis among children under 18 at nearly 10% (CDC 2012) – where steadily increasing prevalence among children has eclipsed rates in adults over the past two decades (Moorman et al. 2012). Of particular concern are persistent, and in some cases widening (Rand and Apter 2008), disparities by race, ethnicity, and poverty status (Moorman et al. 2012; Price et al. 2013); current asthma rates are twice as high among Black children, compared to White (CDC 2012), and poor and minority children have substantively worse morbidity and mortality outcomes (Akinbami et al. 2012).

Asthma is a respiratory airway inflammation disorder, characterized by shortness of breath, wheeze, cough, and airway hyperactivity. Asthma attacks (or exacerbations), during which airways swell and muscle contraction cause difficulty breathing, can be triggered by a range of factors, including infection, immune suppression, exercise, aeroallergens (e.g., pollen, cockroach endotoxin), ambient pollution, stress, diet, and metabolism (Price et al. 2013), and are a leading cause of school absenteeism (Meng et al 2012; Moonie et al. 2006). The severity and frequency of asthma exacerbations vary considerably; while national attack rates among Black versus white asthmatic children do not differ significantly, differences in rates by income, region, and urbanicity are evident (Moorman et al. 2012).

The complex etiology of asthma encompasses biological, structural, social, and environmental pathways, with potential interactions across individual and contextual levels (Schreier and Chen 2013). Risk factors for asthma incidence can be broadly classified across four potentially interacting pathways: genetic and biological, access to healthcare, environmental exposures, and psychosocial factors. Clinical understanding of genetic determinants and heterogeneous phenotypes of asthma, and how they may influence onset, severity, and responsiveness to treatments, is growing (Wenzel 2012), but do not sufficiently explain growing population disparities (Wright and Subramanian 2007). Likewise, disparities in health care access and treatment are well-documented (IOM 2002), however, numerous studies have found that intra-urban disparities remain after adjustment for indicators of health care quality and utilization (e.g., Pearlman et al. 2006), indicating the role of unmeasured, spatially patterned risk factors.

Over past two decades, substantial research attention had been directed toward understanding the role of environmental and social factors in child asthma etiology and disparities. These research avenues have, however, proceeded largely in separate literatures, despite commonalities across hypothesized mechanisms. Toxicants and allergens in the indoor and outdoor environments have been linked with child asthma, operating through oxidative stress (Li et al. 2003), inflammation (Halayko and Amrani 2003), and epigenetic (Kabesch et al. 2010) mechanisms, and reductions in industrial and traffic-related emissions have been identified as an important modifiable risk factors (Friedman et al. 2001; Bernstein et al. 2004). A range of non-chemical exposures have been associated with child asthma, including individual, family, and neighborhood socioeconomic conditions and chronic psychological stress (Chen 2006), also hypothesized to act through inflammatory (Kullowatz et al. 2008), oxidative stress (Ritz and Trueba 2014) and neuro-immune (Marshall 2004) pathways. While both chemical and non-chemical exposures have been implicated in child asthma disparities, neither on their own appear to explain persistent child asthma disparities. Addressing child asthma disparities requires inter-disciplinary research and novel methods for disentangling complex exposure disparities and differential susceptibility, toward identifying modifiable risk factors and public health interventions.

1.1 PSYCHOLOGICAL STRESS & ALLOSTATIC LOAD

Psychological stress – a "real or interpreted threat to physiological or psychological integrity that results in physiological or behavioral responses" (McEwen 2000) – is embodied through a multi-stage process in which an external *stressor* (an event or condition) overwhelms an individual's perceived coping capacity and resources (Cohen 1995). This stress process paradigm highlights the conditional relationship between contextual stressor exposures and individual stress response, mediated by individual appraisal (Figure 1, next page).

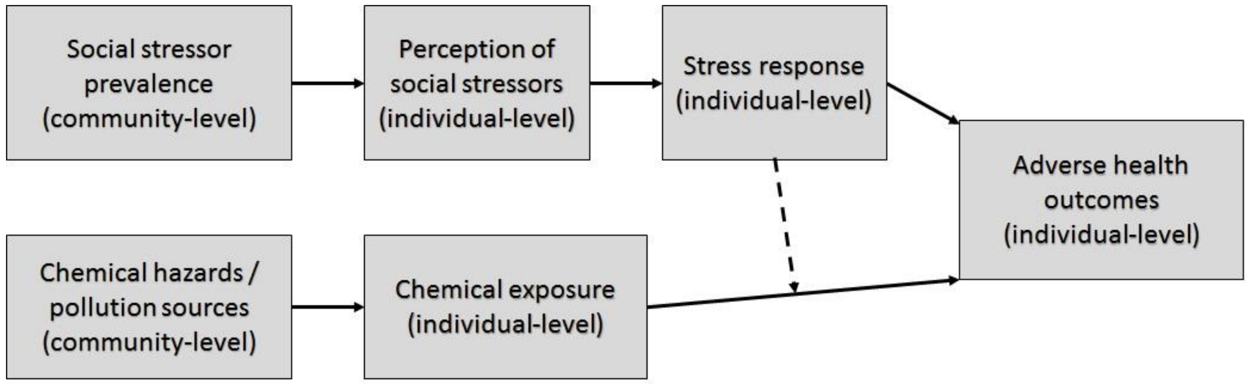


Figure 1. Stress process paradigm and pathways to adverse health outcomes

Chronic psychological stress and maladaptive behaviors influence immune, endocrine, and metabolic function, producing cumulative wear-and-tear and dysregulation of stress response systems – a condition referred to as *allostatic load* (McEwen and Seeman 1999). Over time, allostatic load may alter individuals' reactivity to chemical exposures (e.g., pathogens, pollutants) and increase physiologic susceptibility for multiple disease etiologies (McEwen 2006).

Allostatic load is a robust, biologically plausible mechanism by which chronic social stress may directly impact health outcomes, or influence physiologic susceptibility to chemical exposures in health disparities research. Importantly, physiologic stress response systems are distributed throughout the body and mediated through the brain neurology in a "bidirectional" pathways that are capable of promoting psychological and physiologic resilience as well as ill health (McEwen and Gianaros 2010), suggesting the potential efficacy for interventions targeting psychosocial adaptation.

1.2 URBAN AIR POLLUTION & PSYCHOSOCIAL STRESSORS

There is growing interest in distinguishing separate and combined effects of psychological stress and air pollution on cardiovascular and respiratory health endpoints (Gee and Payne-Sturges 2004; Morello-Frosch and Shenassa 2006; Clougherty and Kubzansky 2009). Toxicology studies have leveraged randomized, controlled exposure designs to demonstrate combined effects of stress and particulate pollution on respiratory function in rats (Clougherty et al. 2010) and inflammatory markers in mice (Bolton et al. 2013). Epidemiologic investigations of modification of air pollution effects on respiratory outcomes by chronic stress have utilized prospective cohort (Clougherty et al. 2007; Shankardass et al. 2009; Islam et al. 2011; Chiu et al. 2013) and cross-sectional (Madrigano et al. 2012; Hicken et al. 2013) designs in multiple US cities, however, not all studies have observed significant interactive effects (Chiu et al. 2013; Hicken et al. 2013). Inconsistencies in epidemiologic findings signal the challenges for characterizing and disentangling complex exposure disparities and differential susceptibility, and point to the need for refined methodologies for measuring and integrating a wide range of urban exposures for social-environmental epidemiology (Clougherty et al. 2014).

Disproportionate exposures to chemical hazards in minority and low-SEP communities is well documented in environmental justice (EJ) literature (United Church of Christ 1987; Bullard 1990; IOM 1999; Morello-Frosch et al. 2011), and considerable attention has been paid to developing geographically-refined methods for assessing disproportionate exposures (Maantay 2002, 2007; Chakraborty 2011). In contrast, there is relatively sparse literature guiding epidemiologists in techniques to characterize and quantify spatial relationships – and potential spatial confounding and effect modification – among distinct, yet potentially correlated, social and chemical stressors (Clougherty and Kubzansky 2009). Social stressors are both *socially* *patterned* (Krieger and Davey Smith 2004; Aneshensel 1992), and *spatially patterned* (Elstad 1998). Multiple social stressors may be concentrated in lower-socioeconomic position (SEP) communities, indicating the potential for confounding and interaction among non-chemical stressors. While lower-SEP communities may be exposed to more (or different) stressful events and conditions than their higher-SEP counterparts (Turner and Avison 2003), it remains unknown the extent to which psychosocial stress acts as a mediating pathway between SEP and susceptibility or health (Matthews and Gallo 2010; Clougherty et al. 2014). As diverse social stressors may be concentrated in lower-SEP communities to varying degrees, and may differently influence health, refined geographic analysis is needed to characterize complex patterning.

Conceptual and analytic challenges for assessing non-chemical exposures are numerous. Regarding data availability and quality, aggregate administrative data is often used to capture a range of community-level social, physical, and behavioral factors in population-level epidemiologic studies. When using these data, the distinction between a *construct* (or idea) of interest (e.g., neighborhood physical disorder) and the multiple imperfect *indicators* commonly used to represent that construct (e.g., percent of buildings with broken windows) is important for epidemiologists because multiple imperfect indicators often exist for each construct, each reflecting different aspects of that construct, and incorporating different patterns of measurement error. A specific challenge for specifying psychosocial stress pathways lies in the fact that perceptions of social stressors are unlikely to be the same across individuals within a community, and thus and may not correlate with objective prevalence measures, while epidemiologists often need to rely on aggregate area-level data covering large urban populations. To this end, understanding the perceptions and priorities of community residents, and validating associations between aggregate stressor indicators (i.e., administrative data) and individual-level perception or stress response, is ultimately needed to identify which contextual social stressors best predict stress-related susceptibility and health.

Analytically, where methods for fine-scale assessment of intra-urban pollution gradients are relatively mature (Jerrett et al. 2005), there is a need to expand social epidemiology approaches for characterizing canonical social determinants of health (e.g., race, income, education) to produce refined assessments of diverse non-chemical stressors. The upsurge in neighborhood effects in public health research since the 1990s (Sampson et al. 2002) has expanded understanding of how contextual exposures (e.g., dilapidated built environment) and social processes (e.g., collective efficacy, social capital) influence health. Neighborhood effects researchers have also focused attention on the challenges of (a) effectively integrating and interpreting geographic information in epidemiology, and (b) disentangling the effects of spatially-confounded exposures – key challenges for elucidating the role of non-chemical stressors in environmental health disparities. Statistically, there is growing concern about spatial confounding among exposures (Sheppard et al. 2012), and growing consideration of spatial autocorrelation, wherein near areas are more similar (thus non-independent) than are far areas (Tobler 1979). The spatial uncertainty resultant from each may exert unknown biases and inflate error in environmental health research (Lorant et al. 2001; Burnett et al. 2001; Pastor et al. 2005; Havard et al. 2009; Chakraborty 2009).

Administrative data (e.g., Census information, land use and zoning, crime statistics) are widely used in public health research to indicate various aspects of the social and physical environment. However, administrative units are imperfect proxies for ‘neighborhoods’ (Diez Roux and Mair 2010) or activity patterns, leading to exposure misclassification and spurious associations due to unit of aggregation, rather than true effects of the exposure of interest. Regarding the use and assimilation of a wide suite of administrative indicators, data are aggregated to multiple area-level units (e.g., Police Precincts, School Districts), introducing challenges for comparing incongruent units of analysis and differing spatial resolution. These issues may extend well beyond well-known issues of ecological fallacy or boundary issues related to the Modifiable Areal Unit Problem (MAUP) (Openshaw 1984; Maantay 2002), and are increasingly explored and well documented in spatial epidemiology (Maantay 2007; Beale et al. 2008) and neighborhood effects research (Chaix et al. 2009). Notwithstanding these challenges, administrative data offer advantages for health research, including consistency of indicator definitions (e.g., felony crimes) and reporting intervals across jurisdictions, facilitating comparisons across space and over time.

1.3 NEW YORK CITY – COMPLEX PATTERNING IN URBAN EXPOSURES

New York City (NYC) is in many ways an ideal setting for observational investigation of separate and combined effects of chemical and non-chemical stressors. NYC's five Boroughs encompass a range of urban environments, densities, multi-ethnic populations, and wide variation in both socioeconomic and physical conditions. Despite overall improvements in the health of New Yorkers over the past twenty years poor non-white residents disproportionately suffer negative outcomes, with stark health disparities by neighborhood wealth (Karpati et al. 2004). A recent NYC health impact assessment estimated that ozone (O_3) and fine particulate ($PM_{2.5}$)-attributable childhood asthma hospitalization rates among are roughly two and three times greater in low versus high poverty neighborhoods, respectively (Kheirbek et al. 2012).

Childhood asthma is longstanding and pivotal organizing issue for community-based organizations and EJ advocates in NYC (Sze 2007). While there are many visions of "environmental justice" – defined by the US Environmental Protection Agency (EPA) as "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" – self-identified EJ campaigns and coalitions in NYC have consistently emphasized environmental racism and democratic involvement of communities of color in decision-making (Sze 2007). Multiple successful campaigns to raise awareness about disproportionate burdens of polluting facilities, including bus depots, incinerators, and waste treatment plants have built a diverse civil society around EJ and health. Previous community-academic research partnerships to understand relationships between air pollution and health built experience with community-engaged research (e.g., Kinney et al. 2000).

1.4 DISSERTATION OBJECTIVES

The overall objective of this dissertation is to apply exposure science principles to develop and validate methods for non-chemical exposure assessment, toward examining differential susceptibility and disproportionate exposures in social-environmental epidemiology. To do so, I aim to integrate community knowledge with theory and methods from environmental and social epidemiology, psychology, and neuro-immunology. From community perspectives, we take a broad view of exposures and triggers implicated in asthma etiology and exacerbation, acknowledging the reality that communities may be burdened with multiple, cumulative exposures. From environmental exposure science, we utilize a spatial approach to characterize variation in population exposures, and contrasts across multiple exposures. From social epidemiology and psychology, we emphasize the need to assess multiple foci of the stress process paradigm, and evaluate multiple components of social environment, with specific attention to distinguishing material socioeconomic and psychosocial pathways that contribute to socioeconomic gradient in health and health disparities. To this end, there are five specific objectives:

1. Utilize spatially-refined exposure metrics to assess effect modification of air pollution-birth weight association by socioeconomic deprivation in NYC.
2. Disentangle spatial relationships and potential confounding among multiple components of socioeconomic position.
3. Expand spatial statistical and geographic information systems (GIS)-based methods for assessing social stressor exposures, and for characterizing interactive effects of chemical and non-chemical stressors.
4. Develop and validate a survey instrument to assess community perceptions of neighborhood geography, using qualitative and quantitative analyses.
5. Estimate associations between stressor prevalence and individual stress perception and response across NYC, toward validating key social stressor measures for epidemiologic analysis.

In Chapter 2, we use a spatially-refined approach for measuring area-level socioeconomic deprivation – a multi-factorial construct hypothesized to operate through psychosocial and material pathways. We build upon an ongoing epidemiologic study of birth outcomes in NYC, which was designed to minimize confounding between social and chemical risk factors, and utilizes fine-scale exposure estimates to reduce exposure misclassification. We evaluate the complex spatial relationship between area-level SEP and air pollution exposures, and leverage detailed individual-level hospital records to examine their separate and combined effects on term birth weight. Gestational exposures and adverse birth outcomes can have myriad health sequelae, particularly regarding chronic diseases (Barker 2002), and this analysis highlights relevant challenges for discerning combined effects of chemical and non-chemical stressors on child asthma. Chapter 2 is in preparation for submission to the *American Journal of Epidemiology*, with co-authors: Kazuhiko Ito, Sarah Johnson, Thomas D. Matte [NYC Department of Health & Mental Hygiene (DOHMH)]; Jennifer F. Bobb, Francesca Dominici (Harvard School of Public Health); Beth Elston, David A. Savitz (Brown University); Zev Ross (ZevRoss Spatial Analysis); and Jane E. Clougherty (senior author, University of Pittsburgh).

In Chapter 3, we implement a spatial approach for assessing chemical and non-chemical exposures across NYC communities. We focus on the methodological and conceptual considerations for integrating chemical and non-chemical stressor data. We focus on area-level social stressors (e.g., rates of violence, residential crowding) which represent chronic exposures, and quantify spatial correlation among multiple social stressor constructs, SEP, and outdoor air pollution across NYC communities. We use GIS-based methods to: a) facilitate (and validate) global comparisons of chemical and non-chemical exposures at different administrative units, and b) explore the effects of unit of aggregation and spatial autocorrelation, towards developing methods for disentangling patterns among spatially-confounded chemical and non-chemical exposures, and ultimately to improve social-environmental epidemiologic study designs. Chapter 3 was published in *Environmental Health* (Shmool et al. 2014).

In Chapter 4, we begin the process of assessing psychosocial exposures through a community-academic partnered focus group study to identify perceptions of neighborhood social and physical stressors across diverse NYC communities. We emphasized recruitment in EJ areas of concern, and asked communities to tell us which neighborhood conditions they felt induce stress (and why) to elucidate residents' ideas of key stressors. Community perceptions were used to develop a locally-appropriate and comprehensive stress survey instrument for NYC. Chapter 4 is in preparation for submission to the *American Journal of Community Psychology*, with co-authors: Michael A. Yonas (Pittsburgh Foundation); Charles Callaway, Ogonnaya Dotson Newman, Evelyn Joseph, Ana Parks, Peggy Shepard (Co-PI) (WE ACT); Laura D. Kubzansky, John D. Spengler (Harvard School of Public Health); and Jane E. Clougherty (PI, University of Pittsburgh).

In Chapter 5, we develop and validate an online survey mapping tool to collect self-defined neighbourhood geography information. We conducted the pilot study in two distinct cities – NYC and Pittsburgh – and evaluated difference in mapping accuracy and concordance with multiple Administrative areas, toward improving assessment of neighbourhood-level social and chemical exposures in epidemiological studies. Chapter 5 is in preparation for submission to the *International Journal of Health Geographics*, with co-authors: Isaac Johnson (University of Minnesota); Rob Keene and Bob Gradeck (University Center for Social and Urban Research); Jane E. Clougherty (PI, University of Pittsburgh).

In Chapter 6, we use survey data to assess relationships between administrative social stressor indicators and individual stress perception and experience across NYC communities, toward developing a validated set of ecologic indicators for use in an epidemiological investigation of the separate and combined effects of social stress and air pollution on childhood asthma in NYC. Chapter 6 is in preparation for submission to *Social Science and Medicine*, with co-authors: Laura D. Kubzansky, John Spengler (Harvard School of Public Health); Ogonnaya Dotson Newman, Peggy Shepard (Co-PI) (WE ACT); Jane E. Clougherty (PI, University of Pittsburgh).

2.0 SOCIOECONOMIC DEPRIVATION, NITROGEN DIOXIDE, AND TERM BIRTH WEIGHT IN NEW YORK CITY

There is considerable attention in environmental epidemiology to the impact of prenatal air pollution exposure on adverse pregnancy outcomes (Shah et al. 2011; Stieb et al. 2012). Despite a growing understanding of the biological mechanisms underlying this association, including systemic oxidative stress (Kannan et al. 2006; Burton and Jauniaux 2011) and inflammation (Munoz-Suano et al. 2011), epidemiological evidence remains inconclusive. This mixed evidence may be attributable to differing exposure assignment methods and measurement error (Dadvand et al. 2013), or to varying co-pollutant exposures and adjustment methods (Woodruff et al. 2009). Alternatively, inconsistencies may arise from incomplete adjustment for confounding, or from differential exposure-response relationships across populations. Of particular concern is sufficiently accounting for socioeconomic deprivation, which may be spatially correlated with air pollution (Tian et al. 2013), and thus confound measures of association, or may operate synergistically through common biological pathways [e.g., chronic stress-induced inflammation and dysregulation of immune and endocrine systems (Clougherty and Kubzansky 2009; Schwartz et al. 2011)].

The need to integrate socioeconomic context and environmental pollution exposures into health research has long been recognized (IOM 1999; Gee and Payne-Sturges 2004; Morello-Frosch and Shenassa 2006), and there is growing attention to the role of multiple exposures and heightened physiologic susceptibility (i.e., allostatic load (McEwen and Seeman 1999)) in driving health disparities (Nweke et al. 2011; Sexton and Linder 2011). There is substantial evidence for adverse impacts of area-level deprivation on pregnancy outcomes, even after accounting for individual socioeconomic position (SEP) (Picket et al. 2002; O'Campo et al. 2008; Blumenshine et al. 2010). However, only a few studies have examined differential effects of air pollution across the socioeconomic gradient, with results ranging from no interaction (Gray et al. 2014), to heightened association among mothers in low SEP areas (Morello-Frosch et al. 2010; Wilhelm and Ritz 2003), to heightened association among mothers in high SEP areas (Généreux et al. 2008). These mixed results may arise from real differences in exposure and susceptibility across populations, or from methodological differences across studies, socioeconomic metrics, or pollution exposure assignment methods. Disentangling the complex relationships between social and environmental exposures requires studies across large and diverse samples, detailed exposure and outcome information, and innovative analytic strategies to address spatial confounding (Ness et al. 2013).

To examine the complex combined effects of air pollution and SEP on birth outcomes, we investigated the joint effect of nitrogen dioxide (NO_2) and area-level deprivation on term birth weight using data from a large birth cohort study. We focus on fetal growth among term births, which has important lifecourse and population health implications (Barker et al. 1992). We build on a study of air pollution and term birth weight in New York City (NYC), designed to minimize spatial and temporal uncertainty in air pollution exposure estimates in a densely populated city with complex patterning in social-environmental exposure contrasts (Savitz et al. 2013; Ross et al. 2013). We previously reported significant associations between urban air pollution [NO_2 and fine particulate matter ($PM_{2.5}$)] and reduced fetal growth (Savitz et al. 2013).

We adapted a composite area-level deprivation index developed for investigations of pregnancy outcomes (Messer et al. 2006) to reflect the spatial heterogeneity of socioeconomic factors across NYC, and adjusted for individual-level SEP. We focus on full-gestation NO_2, which exhibits relatively stable spatial variability across NYC, compared to the more temporally-varying $PM_{2.5}$, because our deprivation metric uses multi-year census variables to maximize precision and spatial resolution in area-level deprivation.,. This is the first study, to our knowledge, to consider non-linear associations between NO_2 and area-level deprivation with birth weight.

2.1 METHODS

This research protocol was approved by the NYC Department of Health and Mental Hygiene Institutional Review Board, and the University of Pittsburgh Institutional Review Board.

2.1.1 Study population

Vital records for 348,585 live births to mothers residing in NYC during 2008-2010 were merged with detailed patient-level data from the New York State Department of Health Statewide Planning and Research Cooperative System (SPARCS), covering admissions to all licensed NYC healthcare facilities. Because we aimed to examine variation in fetal growth, we restricted the study population to full term (37 to 42 weeks gestation), singleton births with no congenital anomalies, born to (self-reported) non-smoking mothers with complete residential address and covariate data, leaving 243,853 births. Exclusion criteria for implausible clinical values and fixed cohort bias (Strand et al. 2011) in this population are detailed elsewhere (Savitz et al. 2013).

2.1.2 Term birth weight outcome and covariates

We examined changes in continuous birth weight among full-term births. We adjusted for individual-level factors previously associated with fetal growth, including: maternal age, pre-pregnancy body mass index (BMI), receipt of prenatal care (yes/no), number of previous lives births, and gestational age (in weeks). We included three measures of maternal SEP: Medicaid status (yes/no), education (< 9, 9 – 11, 12, 13-15, 16, or > 16 years), and race/ethnicity (White, Black, Hispanic, or Asian), by US- and foreign-born status. As in our prior analysis of this data (Savitz et al. 2013), we adjusted for year and season of conception to account for temporal trends in pollution, but did not adjust for outdoor temperature, which was not meaningfully related to term birth weight.

2.1.3 Area-level socioeconomic deprivation

Socioeconomic deprivation encompasses complex conditions of the social and physical environment (Schulz and Northridge 2004; Braveman 2005), calling for composite metrics that capture diverse components of area-level-SEP. Because differences in SEP metrics may limit comparability across studies (Morello-Frosch et al. 2010), we adapted Messer et al.'s (2006) approach. Briefly, Messer et al. developed an area-level derivation index that reflected between-city differences in prevalence in and combinations of SEP indicators using spatially-stratified principle component analysis (PCA). This effort to capture distinct SEP typologies using cities as spatial regimes, or strata, represented an important methodological innovation, as traditional application of data reduction techniques can obscure heterogeneity in SEP patterns (Pickett and Pearl 2001). Here, we adapted this approach to describe intra-urban SEP heterogeneity across

NYC census tracts, and propose a geostatistical technique for identifying optimal spatial strata for PCA.

Table 1. Census SEP indicators used to calculate the SDI

Candidate SEP variables (n = 20) *Source: US Census American Communities Survey (2005-2009)*	***Retained in Spatially-Stratified PCA***	***Retained in City-wide PCA***
Education (among adults aged > 25)		
% < High School		
% BA or more	X	
Employment (among adult labor force, aged 20-64)		
% unemployed	X	X
% males in labor force		
% females in labor force		
Housing		
% renter occupied (among occupied units)		
% vacant housing units (among total housing units)		
% crowded (> 1 occupant per room, among occupied housing units)	X	X
Occupation (among full-time, year-round civilian employed population)		
% adults in management or professional occupations	X	
Income		
% households in poverty (< 200% Federal Poverty Line)	X	
% Families w/ annual income < $35,000 (2009 inflation-adjusted)		
% female householders with children aged < 18		
% households w/ public assistance income	X	
% households w/ Food Stamp benefits (in past 12 months)		
Median household income (in the past 12 months)		
% renter or owner housing costs in excess of 30% household income (in past 12 months)		X
Racial composition		
% African American (non-Hispanic)		X
% non-white (calculated as inverse of non-Hispanic white population)	X	
% Hispanic		
Language		
% speak English less than "very well" (among pop > 5 years old who speak a language other than English at home)		

Based on Messer et al.'s (2006) literature review of census SEP variables previously associated with pregnancy outcomes, we selected twenty indicators covering multiple deprivation domains – educational attainment, employment, occupation, housing, poverty, and racial/ethnic composition – from the American Communities Survey 2005-09 five-year estimates, to best match years of air pollution and birth outcome data (Table 1, previous page). We used census tracts as our unit of analysis, to maximize comparability with other studies of contextual SEP and pregnancy outcomes (Krieger et al. 2003; Janevic et al. 2010). Tracts with total residential population fewer than 20 persons (n = 62 of 2216) were excluded.

To identify spatial strata, which maximized internal correlation of each tract-level SEP indicator, and minimized across-strata correlation, we used Local Indicators of Spatial Association (LISA) statistics to characterize the degree of between-tract clustering. The LISA statistic quantifies the contribution of each tract-level observation to the global spatial pattern, and identifies statistically significant 'clusters' and 'outliers' (Anselin 1995). The LISA term L_i for a given indicator y, at observation i, is expressed as: $L_i = f(y_i, y_{Ji})$, where y_J are 'neighboring' areas J_i of i. Neighbors were defined using a matrix of first-order contiguous areas. Area i can thus be characterized as part of a spatial cluster (i.e., areas surrounded by empirically similar areas), or as an outlier (i.e., areas surrounded by empirically different areas), with 95% statistical confidence. We mapped tract-level LISA terms to visualize areas of spatial non-stationarity (i.e., non-random heterogeneity in spatial trend) for each SEP indicator. We then overlaid candidate spatial strata – administrative neighborhood areas (n = 34), borough boundaries (n = 5), and waterway boundaries – on LISA maps to identify the strata which minimized spill-over (i.e., local cluster boundaries best corresponded with the candidate strata boundaries) (Figure 2, next page). Geostatistical analyses and visualization were implemented in ESRI ArcInfo v10 (Redlands, CA). Based on these data, we identified borough (n = 5) as the optimal strata for describing tract-level SEP heterogeneity across NYC.

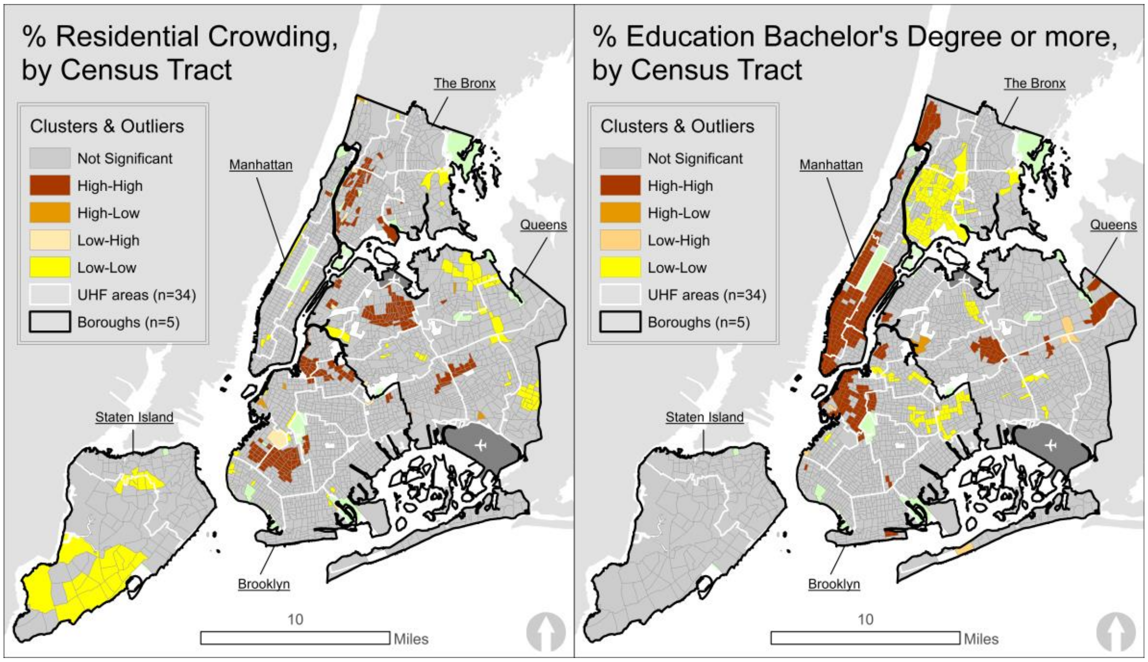


Figure 2. LISA maps of tract-level educational attainment and residential crowding

We followed a standard PCA process to reduce the number of highly-correlated variables to few uncorrelated components. Following initial extraction of components and corresponding eigenvalues, we determined the optimal number of components based on eigenvalues > 1, Scree plots, and proportion of variance > 5%. We then used the rotated (varimax) solution to identify SEP variables that loaded strongly (> ±0.40) on more than one component, suggesting that the variable captured more than one underlying construct, and could be omitted to maximize between-factor differences. After generating a final city-wide PCA solution, we repeated the above steps within each borough, to ensure that locally-important variables and relationships, possibly obscured in the city-wide PCA, could be retained and contribute to the final deprivation index. Specifically, we tallied variables that loaded strongly (> ±0.4) in two or more borough-level PCA solutions. We then ran a second city-wide PCA including variables retained in both the borough-level and initial city-wide solutions, following the same process to iteratively reduce data dimensions.

The socioeconomic deprivation index (SDI) retained seven census SEP variables, including tract-level rates of: residents with a college degree, unemployed, residential crowding, management or professional occupation, below 200% of the Federal Poverty Line (FPL), households receiving public assistance, and non-white racial composition. The first component factor explained 56% of overall variance in retained variables. The initial city-wide solution, in contrast, retained fewer, slightly different variables, and the first component explained only 41% of overall variance (Table 1, page 18). We operationalized the SDI as tract-level factor scores for the first component of the PCA solution, such that higher scores indicated greater socioeconomic deprivation (Figure 3). PCA was implemented in SAS v9 (Cary, NC).

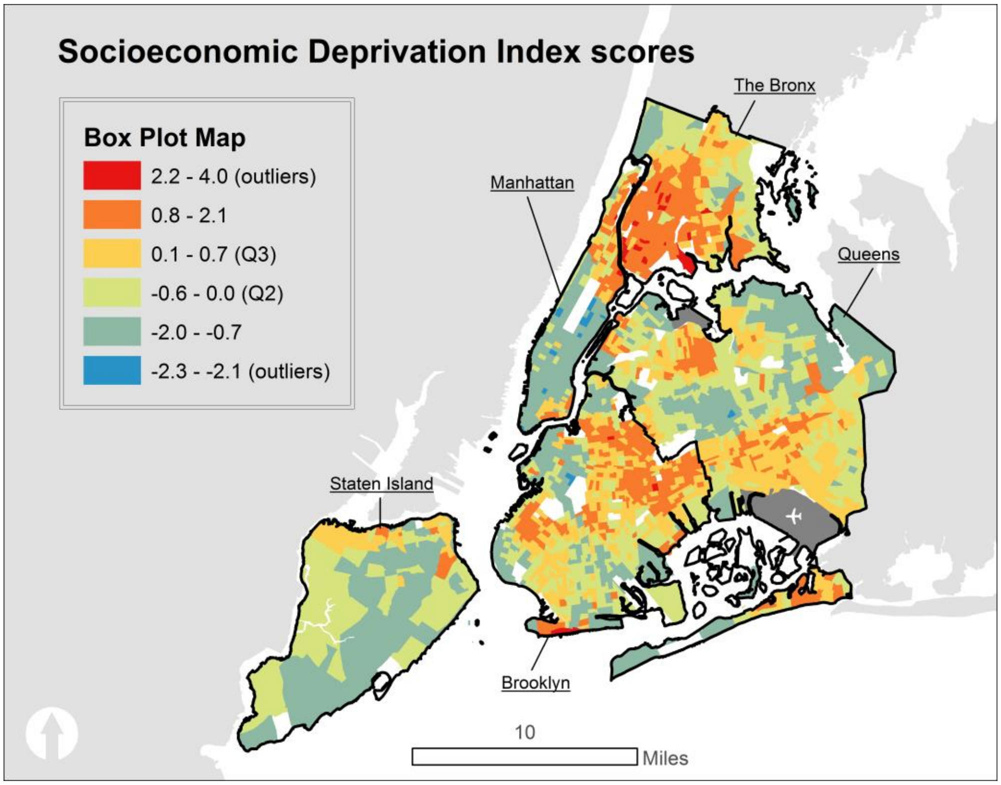


Figure 3. Socioeconomic deprivation index scores

2.1.4 Air pollution exposure

Fine-scale ambient pollution concentration data from the New York City Community Air Survey (NYCCAS) were used to derive near-residence maternal nitrogen dioxide (NO_2) and fine particulate matter (particles with aerodynamic diameter < 2.5 μm^3, $PM_{2.5}$) full-gestation exposure estimates. NYCCAS methods and results are detailed elsewhere (Matte et al. 2013; Clougherty et al. 2013). Briefly, NYCCAS utilized a spatial saturation design to measure multiple air pollutants across 150 locations, repeated during four seasons and multiple years. Monitors were positioned at street-level (10-12 feet), and collected integrated 2-week samples in each season from December 2008 through December 2010. Our prior analysis reported greater spatial variability in NO_2 and greater temporal variability in $PM_{2.5}$ (between sampling seasons and trimesters) (Clougherty et al. 2013; Savitz et al. 2013). Because our SDI measure used multi-year census variables to maximize precision in spatial variability in SEP (and is not time-varying), we focus here on the full-gestation period for NO_2, and consider co-pollutant adjustment for full-gestation $PM_{2.5}$ in sensitivity analyses. Births were geocoded to mother's residential address at delivery, and NYCCAS pollution concentration surfaces (Matte et al. 2013; Clougherty et al. 2013) were used to estimate near-residence exposure as the mean concentration within a 300m radial buffer. Exposure estimates were then temporally adjusted using regulatory monitoring data to match each gestation period, as detailed in Ross et al. 2013.

2.1.5 Statistical analyses and Sensitivity analyses

We used generalized additive mixed models to estimate associations between area-level deprivation, maternal air pollution exposure, and term birth weight, allowing for flexible estimation of non-linear exposure-response relationships using penalized splines (Wood 2003). A random intercept was included to account for the correlation of mothers within a census tract. We first considered a model for birth weight that included independent, non-linear associations of SDI and NO_2 exposure, with linear adjustment for maternal SEP and covariates (Model 1). We then tested interaction between NO_2 exposure and area-level deprivation on term birth weight (Model 2). We used quartile cut-points for interaction models, and combined middle-range SDI quartiles (Q2 and Q3) due to similar observed relationships between pollutant exposures and birth weight in these quartiles. We confirmed these strata as meaningful by re-fitting Model 2 using SDI deciles as interaction strata. Model 2 interaction estimates were also calculated using linear terms to quantitatively compare the estimated slopes across the SDI groups.

We used three sensitivity analyses to improve interpretation of results. First, to confirm that observed modification of the NO_2-birth weight association by area-level deprivation was not driven by within-area composition (i.e., clustering of similar-SEP mothers), we examined modification of NO_2-birth weight association by maternal SEP characteristics, adjusted for area-level deprivation. Second, because NO_2 and $PM_{2.5}$ have some common sources, and thus may be spatially confounded, we re-fit all models with adjustment for maternal exposure to $PM_{2.5}$. Finally, we considered the role of delivery hospital in two ways: (a) as an alternative to considering correlation of mothers within a census tract, we re-fit the models by including hospital of delivery as a random intercept to account for correlation of mothers who delivered at the same hospital, and (b) to account for potential confounding by variation in clinical practices between hospitals (e.g., proclivity to induce labor), we re-fit the models with adjustment for hospital facility. Births included in these hospital analyses were further restricted to exclude facilities with 10 or fewer.

2.2 RESULTS

2.2.1 Population characteristics and exposure distributions

Mothers in the study population represented the socio-demographic diversity of NYC (Table 2, next page), and the geographic stratification of populations by SEP (Figure 3, page 21). Few births were less than 2,500 g (2.64%); these births were slightly less common (2.24%, $p < 0.001$) among mothers in high-SEP tracts (SDI Q1). Overall, 71.5% of mothers reported fewer than 16 years education [roughly the equivalent of a college degree (BA)] and 61.1% of deliveries were eligible for Medicaid coverage. Mothers living in high-SEP tracts (SDI Q1) had higher mean educational attainment (33.5% < BA) and lower mean Medicaid eligibility rates (23.8%), compared to mothers living in lower-SEP tracts (SDI Q4) (92.7% < BA, 83.6% Medicaid eligibility). Overall, 55% of mothers were foreign-born, with the highest proportion of non-native mothers reporting Hispanic and Asian ethnicities. Ethnicity varied across SDI levels; more foreign- and US-born white and foreign-born Asian mothers lived in high-SEP tracts (20.3, 44.3, and 13.5%, respectively), versus higher proportions of foreign- and US-born Black and Hispanic mothers in low-SEP tracts (10.3, 17.7, 36.9, and 20.6, respectively). Mothers in high-SEP tracts were generally older, with lower parity, and lower pre-pregnancy BMI, compared to mothers in low-SEP tracts (Table 3, next page). The majority of mothers received prenatal care.

Table 2. Population statistics, by SDI levels: birth weight, maternal SEP, and air pollution exposures

	Study Population	High SEP tracts (SDI Q1)	Mid-range SEP tracts (SDI Q2 + Q3)	Low SEP tracts (SDI Q4)
	n = 243,853	*n = 60,963*	*n = 121,809*	*n = 61,081*
Term birth weight (g)	*% (n)*	*% (n)*	*% (n)*	*% (n)*
< 1,500	0.04 (88)	0.04 (26)	0.03 (32)	0.05 (30)
1,500 - 2,499	2.6 (6,402)	2.2 (1,361)	2.7 (3,291)	2.9 (1,750)
2500 - 3,999	90.3 (220,156)	90.2 (54,978)	90.3 (110,017)	90.3 (55,161)
≥ 4,000	7.1 (17,207)	7.5 (4,598)	7.0 (8,469)	6.8 (4,140)
Maternal SEP	*% (n)*	*% (n)*	*% (n)*	*% (n)*
Education				
< 9 yrs.	8.1 (19,731)	2.1 (1,300)	8.8 (10,700)	12.7 (7,731)
9 - 11 yrs.	17.6 (42,819)	4.3 (2,622)	17.8 (21,719)	30.3 (18,487)
12 yrs. (~High school)	23.9 (58,286)	10.3 (6,266)	28.4 (35,544)	28.7 (17,476)
13 - 15 yrs.	21.9 (53,376)	16.8 (10,249)	24.9 (30,293)	21.0 (12,825)
16 yrs. (~BA)	16.3 (39,793)	33.2 (20,213)	13.2 (16,129)	5.7 (3,451)
> 16 yrs.	12.2 (29,857)	33.3 (20,213)	6.9 (8,424)	1.8 (1,120)
Medicaid status				
Yes	61.1 (149,106)	23.8 (14,485)	68.6 (83,582)	83.6 (51,039)
No	38.9 (94,747)	86.2 (46,478)	31.4 (38,227)	16.4 (10.042)
Ethnicity				
US-born White	19.4 (47,233)	44.3 (27,021)	14.6 (17,725)	4.1 (2,496)
Foreign-born White	9.4 (22,912)	20.3 (12,387)	8.0 (9,763)	1.3 (762)
US-born Black	12.0 (29,339)	2.8 (1,732)	13.8 (16,779)	17.7 (10,828)
Foreign-born Black	9.8 (23,856)	2.1 (1,295)	13.4 (16,299)	10.3 (6,262)
US-born Hispanic	12.4 (30,346)	6.5 (3,974)	11.3 (13,794)	20.6 (12,578)
Foreign-born Hispanic	21.8 (53,248)	7.4 (4,529)	21.5 (26,161)	36.9 (22,558)
US-born Asian	1.2 (2,899)	2.9 (1,783)	0.8 (981)	0.2 (135)
Foreign-born Asian	14.0 (34,020)	13.5 (8,251)	16.7 (20,307)	8.9 (5,462)
Full-gestation air pollution exposure estimate	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*	*Mean (SD)*
NO_2 near-residence mean concentration (ppb)	26.8 (5.3)	28.1 (8.0)	25.7 (3.9)	27.8 (3.6)
$PM_{2.5}$ near-residence mean concentration (µg/m^3)	11.8 (1.9)	12.3 (2.4)	11.3 (1.5)	12.2 (1.7)

Maternal air pollution exposure varied spatially, and by SDI (Table 2). There were differences in NO_2 exposure estimates across individual-level SEP indicators (results not shown), however the magnitude of differences was small compared to between-SDI differences; mean NO_2 exposure ranged from 25.4 to 29.2 ppb across maternal ethnicity categories, and from 26.4 to 27.4 ppb by Medicaid status.

Table 3. Population statistics, by SDI levels: adjustment covariates

	Study Population	High SEP tracts (SDI Q1)	Mid-range SEP tracts (SDI Q2 + Q3)	Low SEP tracts (SDI Q4)
	n = 243,853	*n = 60,963*	*n = 121,809*	*n = 61,081*
Adjustment covariates	*% (n)*	*% (n)*	*% (n)*	*% (n)*
Maternal age (years)				
< 20	6.6 (16,108)	1.7 (1,024)	6.6 (8,056)	11.5 (7.028)
20 - < 25	20.8 (50,608)	8.1 (4,964)	23.4 (28,504)	28.1 (17,140)
25 - < 30	26.6 (64,814)	20.0 (12,178)	28.9 (35,145)	28.6 (17,491)
30 - < 35	26.4 (64,481)	37.8 (23,062)	24.3 (29,556)	19.4 (11,863)
35 - < 40	15.3 (37,246)	25.1 (15,324)	13.2 (16,025)	9.7 (5,897)
≥ 40	4.4 (10,596)	7.2 (4,411)	3.7 (4,523)	2.7 (1,662)
Pre-pregnancy BMI				
< 18.5 (Underweight)	5.5 (13,445)	6.4 (4,108)	5.3 (6,456)	4.7 (2,881)
18.5 - < 25 (Normal)	54.3 (132,442)	68.7 (41,851)	51.6 (62,810)	45.5 (27,781)
25 - < 30 (Overweight)	23.7 (57,842)	16.3 (9,929)	25.5 (31,082)	27.6 (16,831)
≥ 30 (Obese)	16.5 (40,124)	8.3 (5,075)	17.6 (21,461)	22.3 (13,588)
Prenatal care received				
Yes	99.5 (242,570)	99.6 (60,746)	99.5 (121,156)	99.3 (60,668)
No	0.5 (1,283)	0.4 (217)	0.5 (653)	0.7 (413)
Previous live births				
0	46.6 (113,644)	56.3 (34,314)	44.0 (53,582)	42.2 (25,748)
1	29.5 (71,990)	29.3 (17,884)	29.9 (36,356)	29.1 (17,741)
2	13.5 (33,011)	9.4 (5,727)	14.3 (17,433)	16.1 (9,851)
≥ 3	10.3 (25,208)	5.0 (3,038)	11.9 (14,429)	12.7 (7,741)
Gestational age (weeks)				
37	8.1 (19,654)	7.0 (4,284)	8.6 (10,147)	8.6 (5,223)
38	18.5 (44,994)	17.6 (10,727)	18.7 (22,876)	18.7 (11,391)
39	34.5 (84,237)	35.0 (21,319)	34.7 (41,742)	34.7 (21,176)
40	29.6 (72,284)	31.7 (19,288)	28.7 (35,454)	28.7 (17,542)
41	8.6 (21,002)	8.2 (4,975)	8.8 (10,569)	8.8 (5,368)
42	0.7 (1,682)	0.6 (370)	0.8 (931)	0.6 (381)
Conception season				
Dec - Feb	28.8 (70,242)	28.4 (17,305)	29.0 (35,326)	28.8 (17,611)
Mar - May	20.4 (49,686)	20.0 (12,200)	20.4 (24,839)	20.7 (12,647)
Jun - Aug	22.0 (53,670)	22.4 (13,654)	22.0 (26,787)	21.7 (13,229)
Sep - Nov	28.8 (70,255)	29.2 (17,804)	28.6 (34,857)	28.8 (17,594)
Conception year				
2007	16.7 (40,812)	16.8 (10,212)	16.7 (20,292)	16.9 (10,308)
2008	38.7 (94,238)	38.7 (23,562)	38.6 (47,042)	38.7 (23,634)
2009	37.2 (90,615)	37.2 (22,709)	37.2 (45,301)	37.0 (22,605)
2010	7.5 (18,188)	7.4 (4,480)	7.5 (9,174)	7.4 (4,534)

The inter-quartile range (IQR) for full-gestation maternal NO_2 exposure was 6.25 ppb. NO_2 and $PM_{2.5}$ exposure estimates were correlated (Pearson rho = 0.81), and both were weakly inversely correlated with SDI (NO_2 rho = -0.12, $PM_{2.5}$ rho = -0.11). However, the distribution of NO_2 across the SDI levels exhibited an inverted J-shaped relationship, with highest (and most variable) exposures in the lowest SDI (i.e., most affluent) tracts forming a negative relationship within the lowest quartile of SDI, while, in the mid-to-high SDI tracts (i.e., more deprived), NO_2 and SDI levels showed a weak but positive correlation (Figure 4).

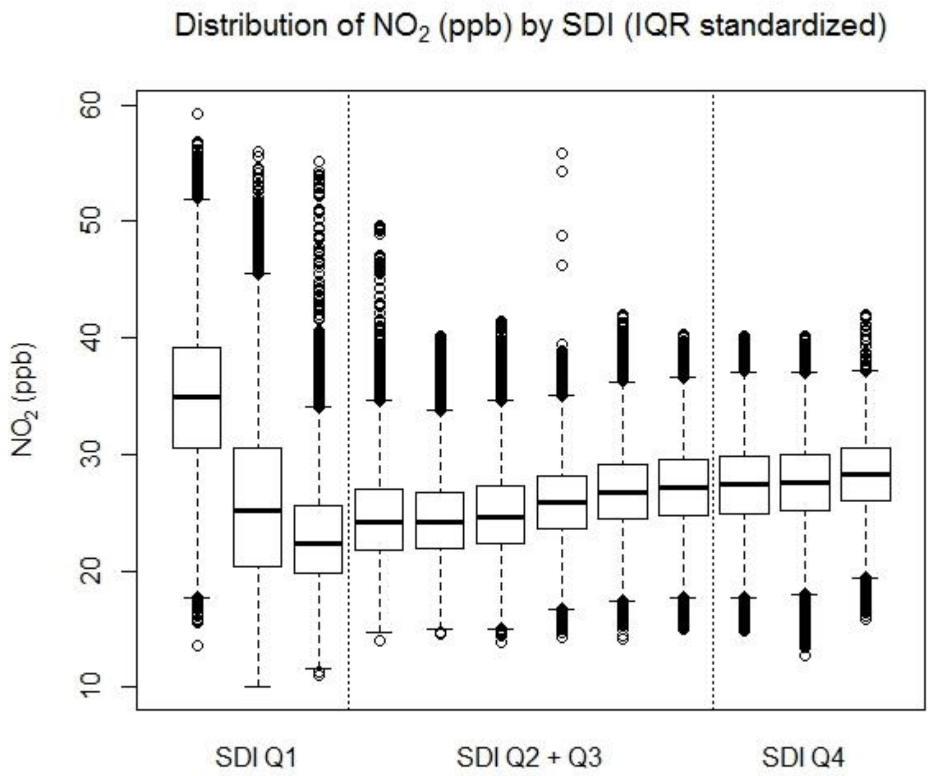


Figure 4. Maternal NO_2 exposure estimates, by SDI

2.2.2 Main effects of NO_2 and area-level deprivation on birth weight

When we considered main effects of area-level deprivation (SDI) and maternal NO_2 on term birth weight, adjusting for covariates (Model 1) in the generalized additive model, SDI levels showed a linear negative association with birth weight, while NO_2 exhibited non-linear negative associations with birth weight. The negative birth weight–NO_2 slope was steeper below approximately 20 ppb, flat between 20 to 30 ppb, and negative but shallow above 30 ppb. (Figure 5, next page).

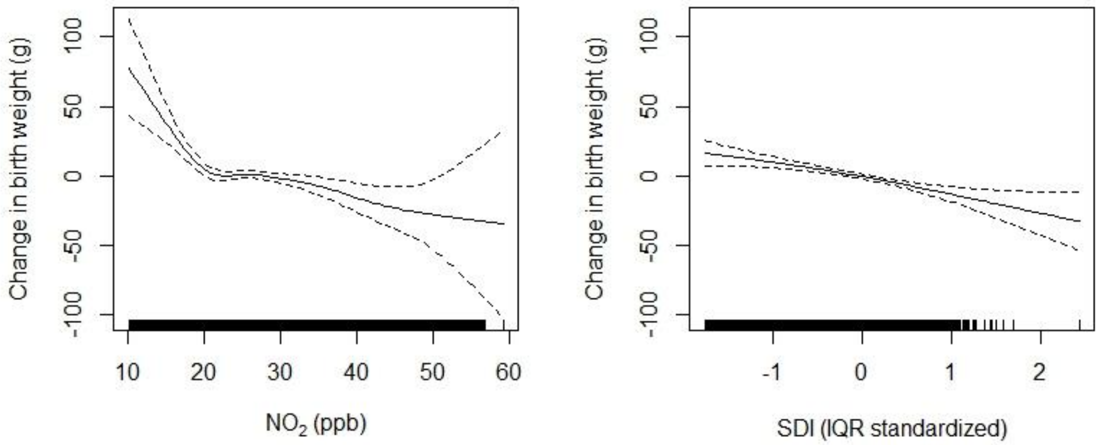


Figure 5. Exposure-response functions (95% CIs) for NO_2- and SDI-birth weight associations, adjusted for maternal SEP and covariates (Model 1)

Gestational age, receipt of prenatal care, pre-pregnancy BMI, maternal age, and maternal education were positively associated with birth weight (Table 4, next page). Offspring of US- and foreign-born Black, US-born Hispanic, and US- and foreign-born Asian mothers had lower average birth weights, as did births in later study years (results not shown), after adjusting for area-level SDI. Medicaid status and conception season were not significantly predictive of birth weight.

Table 4. Linear coefficient estimates and 95% Cis – Models 1 and 2

	Model 1		Model 2	
Covariates	***Change in birth weight (g)***	***95% CIs***	***Change in birth weight (g)***	***95% CIs***
Intercept	2773.4	2746.2, 2800.6	2773.2	2746.0, 2800.4
Ethnicity				
US-born White [REF]	--	--	--	--
Foreign-born White	5.7	-1.2, 12.6	5.8	-1.1, 12.7
US-born Black	-113.8	-121.2, -106.3	-113.3	-120.7, -105.8
Foreign-born Black	-78.5	-86.3, -70.8	-77.9	-85.6, -70.1
US-born Hispanic	-38.2	-45.4, -30.9	-37.9	-45.1, -30.6
Foreign-born Hispanic	-1.4	-8.1, 5.3	-1.0	-7.7, 5.7
US-born Asian	-104.5	-120.3, -88.6	-104.3	-120.2, -88.4
Foreign-born Asian	-87.7	-94.5, -80.8	-87.5	-94.4, -80.7
Maternal education				
< 9 yrs. [REF]	--	--	--	--
9 - 11 yrs.	12.2	10.1, 25.6	12.2	4.9, 19.5
12 yrs. (High school)	17.5	41.0, 57.1	17.5	10.5, 24.6
13 - 15 yrs.	34.7	57.2, 74.2	34.8	27.3, 42.2
16 yrs. (BA)	36.9	66.1, 84.4	37.1	28.8, 45.4
> 16 yrs.	36.1	50.8, 73.6	36.2	27.1, 45.4
Medicaid status				
No [REF]	--	--	--	--
Yes	1.5	4.9, 19.5	1.5	-3.0, 5.9
Maternal age (years)				
< 20 [REF]	--	--	--	--
20 - < 25	17.8	10.4, 24.6	17.8	10.0, 25.5
25 - < 30	49.0	27.3, 42.1	48.9	40.8, 56.9
30 - < 35	65.7	28.6, 45.3	65.5	57.1, 74.0
35 - < 40	75.2	27.0, 45.2	75.1	65.9, 84.2
≥ 40	62.2	-3.0, 5.9	62.1	50.6, 73.5
Pre-pregnancy BMI				
< 18.5 (Underweight) [REF]	--	--	--	--
18.5 - < 25 (Normal)	95.3	87.8, 102.8	95.3	87.8, 102.8
25 - < 30 (Overweight)	159.7	151.6, 167.8	159.7	151.6, 167.8
≥ 30 (Obese)	215.5	207.0, 224.0	215.5	207.0, 224.0
Prenatal care received				
No [REF]	--	--	--	--
Yes	32.2	9.1, 55.2	32.2	9.2, 55.3
Previous live births				
0 [REF]	--	--	--	--
1	68.4	64.3, 72.5	68.4	64.3, 72.5
2	77.2	71.6, 82.8	77.3	71.7, 82.8
≥ 3	76.9	70.3, 83.5	77.0	70.3, 83.6
Gestational age (weeks)				
37 [REF]	--	--	--	--
38	198.8	191.7, 205.8	198.8	191.8, 205.8
39	347.5	341.0, 354.0	347.5	341.0, 354.1
40	454.8	448.2, 461.5	454.9	448.3, 461.6
41	585.9	577.7, 594.1	585.9	577.7, 594.1
42	648.5	627.6, 669.4	648.7	627.8, 669.7

2.2.3 Interaction between NO_2 and area-level deprivation on birth weight

When we modeled modification of the NO_2-birth weight association by SDI levels, adjusted for covariates (Model 2), covariate coefficient estimates were unchanged from Model 1 (Table 4).

We observed decreasing birth weight with increasing pollution exposures in the high- and low-SDI quartiles, but no NO_2 effect in the middle-range SDI group (Q2 + Q3) (Figure 6). Among high area-level SEP tracts (SDI Q1), increasing NO_2 below approximately 20 ppb, and above approximately 30 ppb, was associated with decreased birth weights. Among low area-level SEP tracts (Q4), there was a near-linear negative relationship between NO_2 levels and birth weights. When the interaction between NO_2 and SDI level was modeled with linear terms, the NO_2-birth weight slopes (i.e., birth weight reduction) were -16.2 g (95%CI: -21.9, -10.5), 0.5 g (95%CI: -7.8, 8.8), and -11.0 g (95%CI: -0.9, 22.8) per 10 ppb increase in NO_2, for SDI Q1, SDI Q2 + Q3, and SDI Q4 groups, respectively.

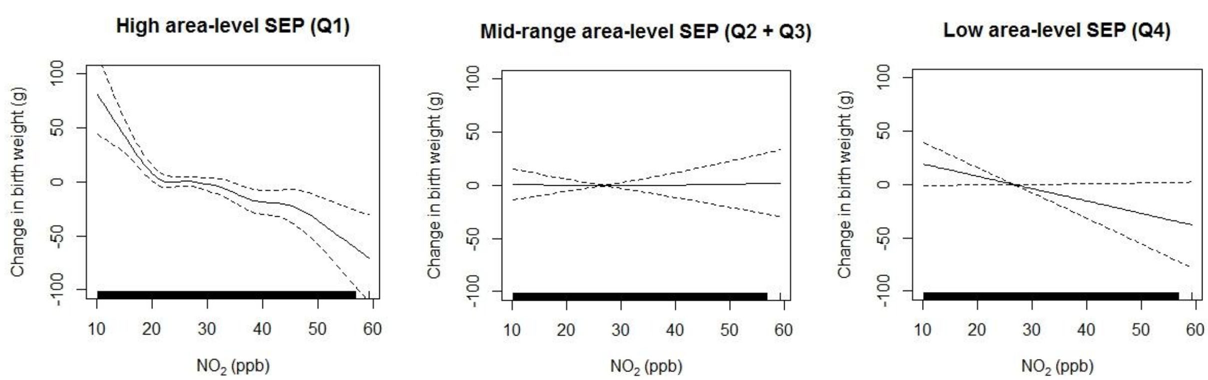


Figure 6. Exposure-response functions (95% CIs) for the interaction between SDI and NO2 on birth weight, adjusted for maternal SEP and covariates (Model 2)

2.2.4 Sensitivity analyses

Tests for modification of the NO_2-birth weight association by individual-level SEP indicators were null or weak (Appendix A). We observed no evidence for modification by maternal education, and modest modification by Medicaid status (p-value = 0.05); among Medicaid-eligible mothers, each 10 ppb increase in NO_2 was associated with a 7.1 g decrement in birth weight, versus a 10.5 g decrement among non-eligible mothers. Similarly, we observed attenuated NO_2-birth weight associations among foreign-born white and Asian mothers (p-value = 0.03 and 0.004, respectively); among foreign-born white and Asian mothers, a 10 ppb increase in NO_2 was associated with 5.0 and 0.3 g decrements in birth weight, respectively, versus 15.8 g decrement among US-born white mothers (referent group).

Adjusting Models 1 and 2 for $PM_{2.5}$ co- exposures did not change coefficient estimates (Appendix A). A smooth term for $PM_{2.5}$ added to Model 1 appeared slightly protective above approximately 20 $\mu g/m^3$, but was not statistically significant. Adding a smooth term for $PM_{2.5}$ to Model 2 did not alter the NO_2-SDI interactions on birth weight.

We tested all models for effects of delivery hospital, as both a potential confounder and clustering variable (i.e., random intercept). In Model 1, we observed a slight attenuation of the SDI-birth weight exposure-response function, but no change in the NO_2-birth weight relationship. In Model 2, we observed similar attenuation of the main SDI-birth weight association, and the NO_2-birth weight association in the lowest deprivation quartile (SDI Q4) became non-significant (results not shown).

2.3 DISCUSSION

Our findings indicate complex patterning of air pollution and birth weight in relation to deprivation in NYC and are in part consistent with previous findings that area-level deprivation may modify the effect of air pollution on fetal growth. The non-linear relationship between maternal air pollution exposure and area-level deprivation we observed in NYC are consistent with the one other NYC analysis of their joint spatial patterning (Hajat et al. 2013), and echo other studies reporting higher air pollution concentrations in more affluent urban areas of Los Angeles County (Molitor et al. 2011) and Rome, Italy (Forastiere et al. 2007). While national- and state-level analyses of deprivation and air pollution across the US indicate that they are generally positively correlated (Bell and Ebisu 2012; Miranda et al. 2011; Tian et al. 2013; Gray et al. 2013), characterizing intra-urban variation and spatial heterogeneity may be important for discerning mixed evidence for the potential role of deprivation as a modifier of air pollution effects on fetal growth.

Our results suggest apparent differences in birth weight decrements along different parts of the exposure-response curve; the relatively steep exposure-response function describing mothers in the most affluent quartile of census tracts (SDI Q1) may be due to higher average near-residence pollution exposures among this group. By comparison, relatively moderate adverse effects were observed across the most deprived quartile of tracts (SDI Q4), where pollution exposures were lower, potentially indicating heightened physiological susceptibility to air pollution (i.e., allostatic load). Alternately, this differential association by SDI may be due to unmeasured deprivation-related behavioral (e.g., time-activity patterns) or structural (e.g., poor resource access) factors, potentially associated with both air pollution and birth outcomes. However, the varying distribution of the estimated NO_2 exposures across SDI levels makes it difficult to call the differences in NO_2/birth weight slopes as “effect modification” or “interaction” (the term whose meaning is most straightforward in a factorial design experiment) because the differences in the slopes may also be due to the difference in NO_2’s variance and concentration ranges.

While few other studies have examined modification of air pollution effects on birth outcomes by area-level SEP, our results are consistent with Généreux et al.’s (2008) finding of an inverse association between maternal residential proximity to highways and size for gestational age only among mothers in the wealthiest areas of Montréal, Canada. By contrast, Wilhelm and Ritz (2003), Ponce et al. (2005), and Morello-Frosch et al. (2010) found heightened associations between air pollution and a range of birth outcomes among mothers residing in lower SEP areas in California. Gray et al. (2014) found increased odds of adverse birth outcomes among Hispanic and Black mothers, compared to white, and among low income census tracts, but found no significant interaction between tract-level mean household income and either $PM_{2.5}$ or O_3, potentially due to low variability in modeled air pollution exposure estimates by area-level SEP across North Carolina. We did not identify any other study to report heightened air pollution effects on birth outcomes among both the high and low deprivation areas. Further studies are needed to understand whether these mixed results are a function of locally-specific differences in exposure and susceptibility patterns, or to different deprivation metrics and/ or air pollution exposure assignment methods. Furthermore, the apparent role of contextual deprivation impacts, as distinct from individual-level and compositional impacts, reinforces the need to design studies to disentangle which components of contextual deprivation may be driving differential susceptibility, and to elucidate their physiological and/ or behavioral mechanisms (Clougherty et al. 2014).

2.3.1 Limitations

Though we sought to minimize uncertainty in exposure assignment, our air pollution exposure assessment was limited because near-residence estimates do not encompass daily activities, and assume that the mother maintained the same residential location recorded at the time of birth for full gestation. Though we tested adjustment for co-pollutant $PM_{2.5}$ exposure, our use of the total mass concentration, instead of specific constituents, may have obscured impacts of key elevated $PM_{2.5}$ constituents in NYC, the spatial distributions of which may not be accurately captured by the total mass distribution [e.g., nickel (NYC DOHMH 2010)]. Likewise, our area-level deprivation assessment was conducted using census tract units, which may be poor proxies for lived neighborhood spaces (Diez Roux 2001).

2.3.2 Strengths

The primary strength of this analysis is our fine-scale, spatially-informed exposure assignment for both air pollution and contextual deprivation. Here, we propose the identification of spatial regimes as a novel approach for improving accuracy and local-specificity in the estimation of contextual deprivation, which may be of particular interest in studies of joint effects of social and environmental exposures. Importantly, spatial regimes can be identified and evaluated empirically using geostatistical techniques (e.g., LISA) commonly used in the field of econometrics (Paelinck and Klaassen 1979; Anselin 2009), and more recently in air pollution modeling (Sampson et al. 2013). These methods offer promising approaches for environmental health researchers, especially where exposure-outcome relationships may be heterogeneous across space. We adjusted for multiple maternal SEP indicators, and tested whether our observed area-level deprivation modification was driven by compositional, rather than contextual, factors. In keeping with the “ethnic framework” for birth outcomes research (Janevic et al. 2010), we included both maternal ethnicity and nativity (i.e., US- vs. foreign-born).

2.4 CONCLUSION

Our findings suggest possible differential associations between air pollution and fetal growth by contextual socioeconomic deprivation, but also illustrate the complexity in determining the "interaction" of these risk factors because of their uneven joint distribution, and overall highlight the importance of characterizing fine-scale spatial heterogeneity among social and environmental conditions. Spatially-refined exposure assessment and a flexible modeling approach revealed where adverse birth outcomes may arise from disproportionate exposure burdens, or from differential susceptibility to exposures. Further studies are necessary to elucidate which components of deprivation – material or psychosocial – may increase physiological susceptibility to pollution exposures.

3.0 SOCIAL STRESSORS AND AIR POLLUTION ACROSS NEW YORK CITY: A SPATIAL APPROACH FOR ASSESSING CORRELATIONS AMONG MULTIPLE URBAN EXPOSURES

Within the field of environmental health, there is substantial interest in the combined effects of chemical and non-chemical exposures on human health (Gee and Payne-Sturges 2004; Morello-Frosch and Shenassa 2006; Nweke et al 2011; Sexton and Linder 2011). Recent epidemiologic and toxicologic evidence indicates significant modification of pollution effects on health by chronic psychosocial stress (Clougherty et al. 2007; Peters et al. 2007; Virgolini et al. 2008; Shankardass et al. 2009; Clougherty et al. 2010; Cory-Slechta et al. 2010; Zota et al. 2013; Hicken et al. 2013). For investigators interested in understanding the relationship between the social and physical environment, there is a growing need for refined, replicable methods for: a) measuring social stressor exposures across large cohorts, and b) reducing confounding between social and chemical exposures in environmental epidemiology (Clougherty and Kubzansky 2009).

Recent research on this topic has considered psychosocial stress as a possible key factor modifying the relationship between chemical exposures including air pollution or lead, and adverse health outcomes (Clougherty et al. 2014). As such, individuals and communities who are chronically exposed to social stressors may be more susceptible to adverse health effects of environmental chemicals. The field of stress measurement primarily relies on individual questionnaire or biomarker data to assess the occurrence of stressful events (Attar et al. 1994), conditions that might produce stressful experiences (Ross and Mirowsky 1999), recent perceptions of stress (Cohen et al. 1983), or the mental health sequelae of chronic stress (i.e., depression, anxiety).

In contrast, large epidemiological studies that seek to evaluate whether chronic psychosocial stress increases susceptibility to chemical exposures are often unable to assess stress at the individual-level. As a result, they often rely on administrative indicators (e.g., crime, poverty rates) uniformly assessed across heterogeneous communities, as proxy measures to capture the presence of social stressors (e.g., lack of neighborhood safety, financial stress), and, by extension, psychosocial stress. Based on evidence that psychosocial stress levels are high in low SEP areas (Adler et al. 1994; Baum et al. 1999), most epidemiological studies of combined social and environmental effects have primarily used census-derived socioeconomic position (SEP) and demographic measures as a proxy for both a range of social stressors and for psychosocial stress *per se* (Clougherty et al. 2014). Few studies have tested the assumption that SEP indicators are an appropriate proxy. As a result, it remains unclear how well SEP indicators capture exposure to social stressors and psychosocial stress; if these indicators are, in fact, weak proxies, it would limit the interpretability of contextual SEP effects, and hamper identification of possible causal mechanisms. As an alternative approach, some studies aiming to focus on psychosocial stress have examined other single social stressors, choosing stressors that are unlikely to be appraised positively [e.g., exposure to violence (Clougherty et al. 2007)]. Both approaches suffer from unmeasured confounding insofar as they cannot account for, or distinguish amongst, the constellation of social stressors that can contribute to differential physiological susceptibility to chemical exposures.

Spatial correlation, or common clustering between distinct exposures – and discerning its impact on possible confounding and effect modification – is a key measurement challenge for social-environmental epidemiology. For example, traffic-related air pollution may be inherently confounded by traffic-related noise (Allen et al. 2009; Ross et al. 2011), complicating the interpretability of effects for either exposure. Combining data on multiple social stressors addresses some of the concerns identified above, but a further methodological challenge is that publicly-available indicators are often aggregated to different administrative spatial scales, by data source and type (i.e., police precincts, census tracts). Moreover, a number of different stressor indicators for the same construct may be available (e.g., multiple felony crime indicators – assault, robbery, or burglary), and it remains under-explored how well each of these various stressor indicators captures the intended psychosocial construct. As such, using only a single indicator of that construct may or may not be sufficient for capturing spatial distributions in these exposures. Thus, with reproducible geo-statistical methods to elucidate common spatial variation in social stressors and chemical exposures across large cohorts, we will improve our ability to reduce confounding and design studies appropriately powered to disentangle separate and combined effects.

Here, we present a spatial approach for characterizing co-varying social and environmental exposures. To demonstrate this approach, we use refined geographic analyses to examine intra-urban relationships across multiple exposures in New York City (NYC), where social, economic, and physical environmental conditions vary widely. Exposure data are drawn from multiple publicly-available administrative databases to capture dimensions of the social environment, and air pollution data are from the New York City Community Air Survey (NYCCAS). We quantify spatial relationships across this broad set of social stressor indicators, and between these stressor indicators and air pollution. We use geographic information systems (GIS)-based methods to: a) facilitate comparisons across different, incongruent administrative areal units, and b) explore potential effects of areal unit and spatial autocorrelation on observed associations between stressors and air pollution. Finally, we present an exploratory ecologic analysis of spatial confounding and effect modification by social stressors in the relationship between nitrogen dioxide (NO_2) and childhood asthma exacerbations, to illustrate the risks associated with mis-specification of spatially-patterned exposures and susceptibility.

3.1 METHODS

3.1.1 Outdoor air pollution data

The New York City Community Air Survey (NYCCAS) is a surveillance program of the NYC Department of Health & Mental Hygiene (DOHMH), designed to inform local air quality initiatives. Spatial saturation monitoring was performed year-round across all NYC communities; study design and protocols have been explained in detail elsewhere (Matte et al. 2013). Land Use Regression techniques were used to model intra-urban variation in ground-level fine particulate matter ($PM_{2.5}$), black carbon (BC), nitrogen dioxide (NO_2), wintertime sulfur dioxide (SO_2), and summertime ozone (O_3) (Clougherty et al. 2013). Fine-scale pollutant concentration surfaces were averaged to five administrative units (UHF, CD, PP, SD, USCT), for comparability with social stressor indicators (Figure 7).

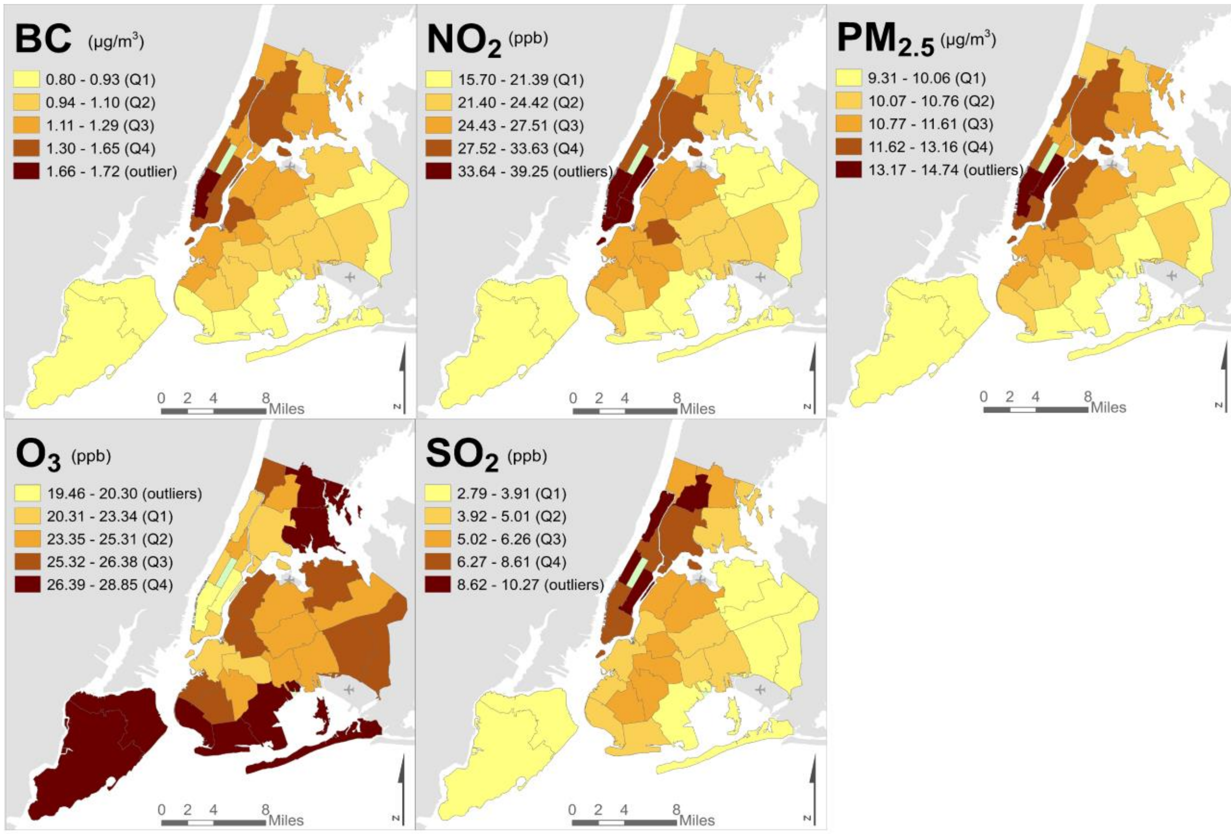


Figure 7. Maps of NYCCAS 2008-2009 area-level average pollution concentrations, by UHF

3.1.2 Area-level social stressor data and aggregation

We identified 29 administrative indicators that may provide information on exposure to social stressors collected by NYC government agencies and the US Census Bureau (Table 5, page 42; Figure 8, next page). Administrative indicators of social stressors were reported at five areal units: Police Precincts (PP) (n = 74), Community Districts (CD) (n = 59), United Health Fund areas (UHF) (n = 34), School Districts (SD) (n = 32), and census tracts (USCT) (n = 2,111). We obtained multiple indicators to capture each stressor construct, to evaluate whether indicators for the same constructs follow similar spatial patterns; for example, under 'physical disorder,' we explored five different indicators, to enable exploration of both within-construct and between-construct spatial heterogeneity. Administrative indicators were selected to capture key social stressors as identified by focus groups (Carr et al. 2012) and by prior literature, including: violence and crime (Sampson et al. 1997), neighborhood disorder (Ross and Mirowsky 1999; Evans 2003), and noise (Evans et al. 2003). Inclusion criteria for the current study required: a) reliable and uniform data quality and interpretability across all communities, b) citywide coverage, and c) approximately concurrent temporality with air pollution data (2008-2010). We included Census-derived area-level SEP and racial composition indicators, to examine how these indicators might co-vary with administrative indicators of social stressors. We excluded indicators with known biases [e.g., differential reporting of and conviction for felony rape (Walker et al. 2012)] or complicated interpretability with respect to chronic stress (e.g., green space may represent access to recreation, or perceived unsafe areas).

Table 5. Social stressor constructs indicators

Stressor Construct	Administrative Indicator	NYC Agency Administrative Data Source	Scale	Date
Crime & Violence	Felony Larceny Crimes	Police Department (NYPD)	PP	FY2009
	Murder and non-negligent manslaughter	NYPD	PP	FY2009
	Felonious Assault	NYPD	PP	FY2009
	Felony Robbery	NYPD	PP	FY2009
	Felony Burglary	NYPD	PP	FY2009
	Perceived Lack of Neighborhood Safety [self-report (SR)]	DOHMH Community Health Survey (CHS)	UHF	2010
Physical Disorder	Small parks not acceptably clean	Parks Department	CD	FY2009
	Sidewalks not acceptably clean	Mayor's Office of Operations (MOoO)	CD	FY2009
	Serious housing violations	Dept. of Housing Preservation and Development	CD	2009
	Air Quality complaints	NY State Department of Environmental Protection	CD	FY2009
	Crowding (>1 occupant/room)	US Census American Community Survey (ACS)	USCT	2005-09
Access to Healthcare	No insurance coverage (SR)	CHS	UHF	2009
	Went without needed medical care (SR)	CHS	UHF	2009
	Without personal care provider (SR)	CHS	UHF	2009
	Public Health Insurance enrollment	MOoO	CD	FY2009
Noise disruption	Frequent noise disruption (3+ times/wk) (SR)	CHS	UHF	2009
	Noise disruption, by neighbors, traffic (SR)	CHS	UHF	2009
School-related stressors	Students in schools exceeding capacity	Department of Education (DOE)	SD	2006-07
	School buildings in good to fair condition	DOE	SD	2006-07
	Average daily student attendance	DOE	SD	2006-07
	Substantiated cases of Child Abuse/Neglect	Administration of Child Services	CD	2009
Socioeconomic Position (SEP)	Living below 200% Federal Poverty Line	ACS	USCT	2005-09
	Delayed rent or mortgage payment in past year (SR)	CHS	UHF	2009
	Food Stamp program enrollment	MOoO	CD	FY2009
	Less than high school education (SR)	CHS	UHF	2009
	Unemployed < 1 year	ACS	USCT	2005-09
	Non-White racial composition	ACS	USCT	2005-09
	African American (Non-Hispanic) racial composition	ACS	USCT	2005-09
	Hispanic ethnic composition	ACS	USCT	2005-09

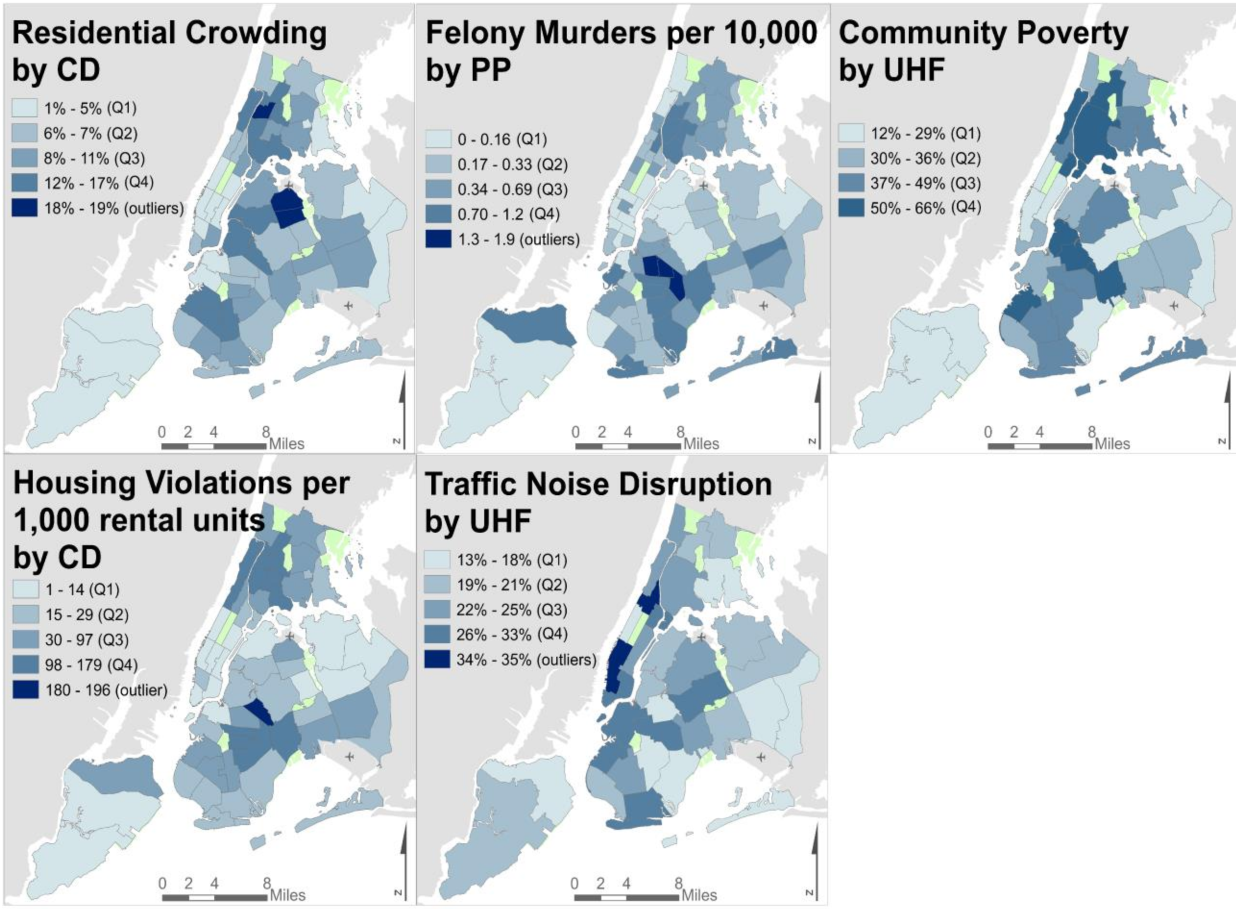


Figure 8. Maps of administrative indicators of social stressors, by differing areal units

To address the challenge of multiple administrative areal units, we applied GIS-based techniques to derive and validate area-weighted prevalence estimates at a common unit of analysis. First, we calculated percent geographic overlap between all administrative units to derive proportional-coverage weights matrices, then reformulated all stressor indicator prevalence to UHF (the reporting unit for hospital admissions and health survey data), to enable correlation analysis across indicators (Figure 9, next page). We chose an area-based technique, rather than population density-based, to maximize interpretability, as we have no evidence that stressor prevalence varies in proportion to population density. We aggregated census data from tracts to UHF areas based on centroid containment, excluding tracts with fewer than 20 residents.

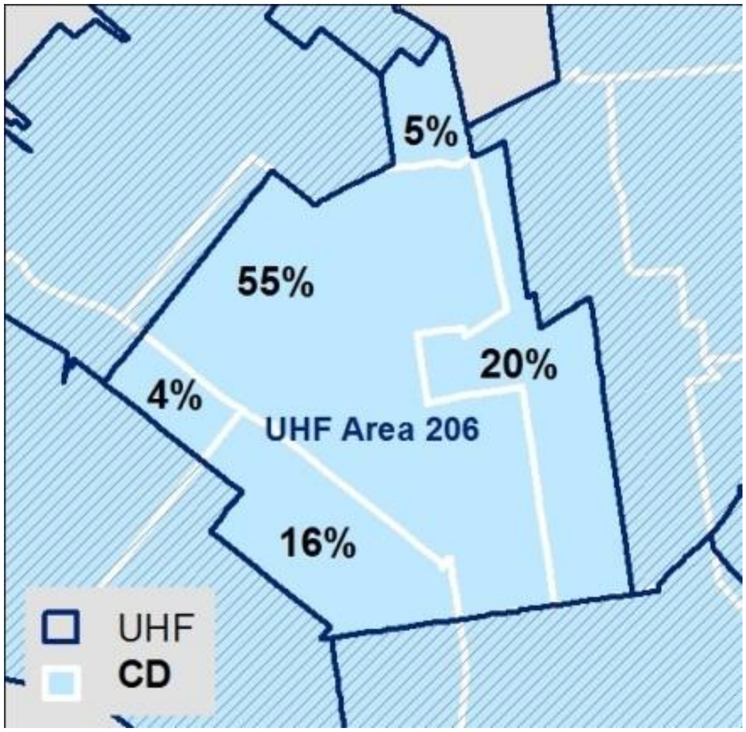


Figure 9. Areal weighting by proportional coverage

Because the above areal weighting method cannot account for within-area variation in aggregate data, we introduce a technique quantifying the potential for exposure misclassification due to areal averaging. Using three high-resolution NYCCAS continuous (smooth) pollution surfaces with differing spatial patterns ($PM_{2.5}$, SO_2, and O_3), we calculated mean concentrations at multiple administrative units (CD, PP, SD, and UHF). We then applied the same areal weighting method to reformulate concentrations at CD, PP, and SD to UHF units, enabling a comparison of reformulated mean concentrations to the original, ‘known’ area-level concentrations. For this validation, we do not assume that pollution patterns reflect stressor patterns – rather, these three different smooth surfaces (known spatial processes) merely enable analysis of the reproducibility of areal reformulation across administrative units. Figure 10 (next page) shows kernel density plots comparing mean wintertime $PM_{2.5}$ and SO_2, and summer O_3

concentration distributions by UHF, versus concentrations recalculated at other administrative units. Using a percent-error tolerance of 5%, and examining similarity in the density distribution we found that CD and PP units were reasonably reformulated to UHF for global analysis, but SDs (the largest spatial unit) were not. In sensitivity analyses, we confirmed that detection of autocorrelation was consistent between original units and reformulated values. Calculations were performed in ESRI ArcGIS, v10, and R Statistical Software, v2.11.

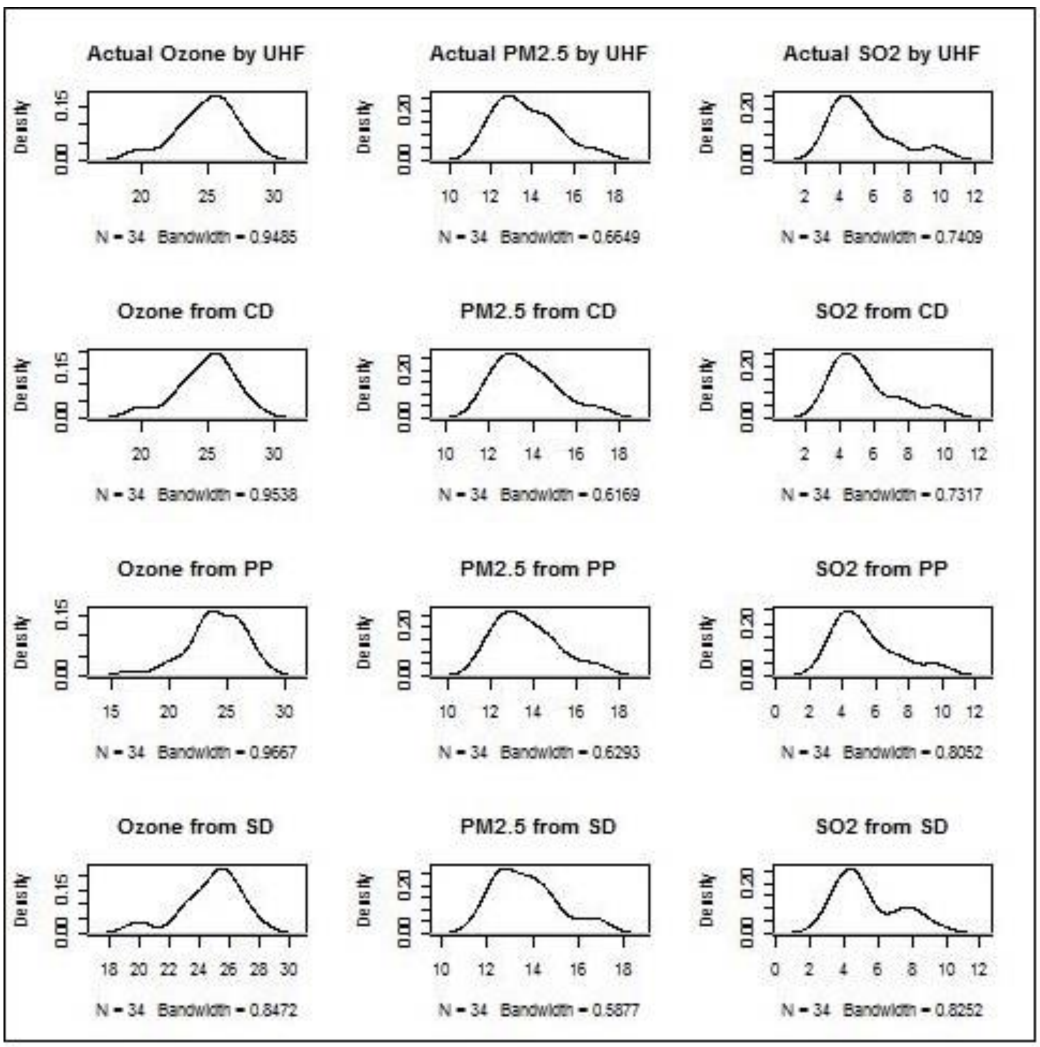


Figure 10. Kernel density plots comparing actual versus reformulated area-average pollutant concentrations

3.1.3 Spatial autocorrelation

We examined potential impacts of spatial autocorrelation – the geographic principle that near areas are more similar than are far areas (and thus non-independent) (Tobler 1979) – on bivariate measures of association between area-level exposures. Autocorrelation structures can be operationalized in statistical models as spatial weights (W_{ij}), wherein either centroid distance or contiguity (i.e., shared boundaries) is quantified for each observation pair. Given NYC's irregularly-sized and shaped administrative units, we used first-order (Queen) contiguity, wherein areas sharing *any* boundary are neighbors ($W_{ij} = 1$), else non-neighbors ($W_{ij} = 0$). We used the Moran's I statistic to detect non-random spatial clustering in each variable (as summed cross-products of deviations between neighboring units, and deviation from overall mean) (Moran 1950). We sensitivity-tested spatial weights using inverse distance between all areal unit centroids.

We then examined potential impacts of spatial autocorrelation in bivariate Simultaneous Autoregressive (SAR) models, which apply spatial weights and Moran's I to identify model misspecification, potentially due to spatial dependence, in Ordinary Least Squares (OLS) residuals. Where appropriate, we used SAR to derive pseudo-r values (Anselin 2005), which, though not directly comparable to Pearson rho values (i.e., do not represent proportion of variance explained), do effectively rank shared variance across covariates. Additional spatial regression techniques and SAR model specification are detailed in Appendix B. While most stressors displayed spatial clustering across area units, only 20% of bivariate OLS comparisons revealed residual autocorrelation, calling for SAR. As most (88%) of SAR pseudo-r values did not differ substantially from OLS rho values, we report OLS as the main results here. SAR results (i.e., spatial error vs. lag models) are reported in Appendix B.

3.1.4 Correlation analyses

We characterized intra-urban variability and quantified spatial correlations across social stressors, and between stressors and pollution, using Pearson correlation coefficients and SAR pseudo r-values, calculated at the original area unit (for covariates reported at the same administrative unit), else at UHF. To identity suites of social stressors which co-vary spatially, we used exploratory factor analysis (EFA) including all stressors aggregated to UHF. We used orthogonal (varimax) rotation, and identified the optimal number of factors using scree plots, covariance eigenvalues, and factor interpretability.

To evaluate whether the factor solution was driven by data density (i.e., number of indicators available within each construct), or covariance due to shared substantive or spatial variance across stressor variables, we employed multiple sensitivity analyses: 1) we separately removed five "redundant" indicators within constructs (rho $\geq$ 0.8) to ensure that the factor solution were robust to imbalance in number of indicators by construct, and 2) because some indicators may not solely indicate psychosocial stress pathways (e.g., noise exposure may act through auditory pathways), we separately removed each, then repeated analyses. Sensitivity analysis for autocorrelation impacts on measures of association revealed that our data did not require adjustment for spatial dependence in factor analysis [e.g., (Hogan and Tchernis 2004)]. Analyses were performed in ESRI ArcGIS v10, OpenGeoDa v0.9.9.14, and R v2.11.

3.1.5 Ecologic analysis: Social stressors, NO_2, and child asthma exacerbation

The primary objective of this ecologic analysis is to demonstrate how this spatial approach can be operationalized, and to explore the potential impacts of social stressor indicator selection or spatial mis-specification in stressor patterns, for social-environmental analyses. From the EFA, we identified suites of spatially-correlated stressors (factors) and derived factor scores for each UHF area. Factors were then examined as potential effect modifiers in the relationship between UHF-level mean NO_2 concentration and asthma Emergency Department (ED) visit rates for children aged 0-14 years during 2008-2010 [from the New York State Department of Health Statewide Planning and Research Cooperative System (SPARCS)]. We used single-predictor and multi-variable SAR models to evaluate the relationship between a cross-sectional ecologic exposure (i.e., NO_2) and child asthma ED visits by UHF. To examine potential modification of NO_2 effects by stressor factors, we stratified the 34 UHF areas at the median factor score, and sensitivity-tested models stratifying each factor at a score of 0.

3.2 RESULTS

3.2.1 Correlations among social stressors

We identified significant intra-urban variability and spatial autocorrelation within both social stressor indicators and pollutant concentrations (Table 6, next page).

Table 6. Area-level summary statistics

Administrative Indicator	Mean	Min	Max	SD	Moran's I†
Felony Larceny Crimes/ 10,000 persons	50.89	17.01	457.69	57.90	0.38**
Murder/ 10,000	0.43	0.00	1.85	0.37	0.46**
Felonious Assault/ 10,000	15.46	1.82	42.34	9.00	0.39**
Felony Robbery/ 10,000	19.59	3.08	48.68	9.11	0.34**
Felony Burglary/ 10,000	18.48	5.52	93.70	10.52	0.14*
% Perceived Lack of Neighborhood Safety	30.39	4.70	64.70	16.93	0.25*
% Parks not acceptably clean	20.46	0.00	51.00	11.52	0.34**
% Sidewalks not acceptably clean	3.07	0.20	10.80	2.16	0.52**
Serious housing violations/ 1,000 Units	53.87	1.40	195.80	51.11	0.57**
Air Quality complaints/ 10,000	12.50	3.87	56.76	11.89	0.70**
% Crowding	7.95	1.73	16.28	3.67	0.24*
% With no insurance coverage	15.42	2.94	29.62	5.69	0.31*
% Went without needed medical care	11.56	3.58	19.68	3.79	0.20
% Without personal care provider	16.45	8.12	32.36	5.96	0.08
Public Health Insurance enrollment	2801.64	417.10	5356.22	1274.07	0.41**
% Frequent noise disruption	19.86	11.38	35.33	5.81	0.08
% Traffic noise disruption	21.91	12.98	35.21	5.61	0.07
% Neighbor noise disruption	19.63	7.86	30.32	5.28	0.09
% Students in schools exceeding capacity	16.00	0.00	41.70	12.81	0.10
% School buildings in good to fair condition	33.16	1.00	57.00	12.00	0.14
% Average daily student absenteeism	9.94	6.67	14.75	1.86	0.41**
Cases of Child Abuse/ Neglect	26.84	2.69	87.82	21.95	0.62**
% Living below 200% federal poverty	37.16	12.15	65.82	13.04	0.32*
% Delayed rent or mortgage payment	15.78	4.99	29.43	6.86	0.25*
Food Stamp program enrollment/ 10,000	1638.20	186.31	3888.49	1040.26	0.54**
% Less than high school education	13.47	2.80	35.70	8.10	0.10
% Unemployed < 1 year	8.38	4.38	14.24	2.44	0.55**
% Non-White racial composition	63.32	20.34	97.98	23.31	0.28*
% African American (Non-Hispanic)	23.31	1.64	72.62	22.54	0.35*
% Hispanic ethnicity composition	26.25	6.33	64.67	16.80	0.53**
Mean pollution concentration, by UHF	**Mean**	**Min**	**Max**	**SD**	**Moran's I**
BC (abs)	1.12	0.80	1.72	0.22	0.57**
NO_2 (ppb)	25.13	15.70	39.25	5.20	0.57**
$PM_{2.5}$ ($\mu g/m^3$)	11.08	9.31	14.74	1.29	0.56**
SO_2 (ppb)	5.40	2.79	10.27	1.94	0.52**
O_3 (ppb)	24.85	19.46	28.85	2.19	0.43**

* indicates statistical significance at $p < 0.01$, ** $p < 0.0001$

† Moran's I values near zero indicate random dispersion; positive values indicate spatial autocorrelation

Social stressors were not consistently correlated with each other, even within construct (e.g., among indicators intended to capture similar aspects of the social environment) (Table 7, next page). For example, rates of self-reported noise disruption varied by noise source, and noise from traffic and from neighbors were highly uncorrelated (rho = 0.01). Likewise, correlations among indicators of community SEP varied widely (rho = -0.05 to 0.89). Stressor indicators related to crime and safety were strongly positively correlated, except for those related to property crimes (i.e., larceny, burglary).

Table 7. Correlation among social stressor indicators

	Larceny	Murder	Assault	Robbery	Burglary	Safety	Child abuse/ neglect	Parks unclean	Sidewalks unclean	Serious housing violations	Air quality complaints	Crowding	No insurance	Without needed care	No medical provider	Public health insurance	Freq. noise disrupt	Traffic noise disrupt	Neighbor noise disrupt	Delayed rent/ mortgage	Food Stamp enrollment	Less high school education	Unemployed	Poverty	% Non-White	% African American	% Hispanic
Larceny	**1**																										
Murder	−0.13	1																									
Assault	0.23	**0.68**	1																								
Robbery	0.33	**0.60**	**0.89**	1																							
Burglary	**0.84**	0.13	0.40	0.50	1																						
Safety	−0.33	**0.73**	**0.82**	**0.73**	−0.06	1																					
Child abuse	−0.23	**0.70**	**0.85**	**0.70**	−0.01	**0.85**	1																				
Parks unclean	−0.44	0.20	0.05	0.02	−0.26	0.15	0.07	1																			
Sidewalks unclean	−0.16	**0.74**	**0.64**	0.59	0.41	**0.65**	0.58	0.10	1																		
Housing Violations	−0.26	**0.66**	**0.71**	**0.62**	0.08	**0.84**	**0.67**	0.09	0.55	1																	
Air quality complaints	**0.84**	−0.34	−0.05	0.03	0.43	−0.37	−0.36	−0.38	−0.26	−0.36	1																
Crowding	−0.21	0.17	0.25	0.30	0.22	0.39	0.27	0.14	0.48	0.46	−0.20	1															
No insurance	−0.35	0.21	0.21	0.18	−0.22	0.51	0.28	0.30	0.38	0.5	−0.43	**0.63**	1														
Without care	−0.30	0.41	0.41	0.39	0.03	0.53	0.38	0.15	0.35	**0.63**	−0.29	0.34	0.50	1													
No provider	−0.03	0.09	0.22	0.22	0.09	0.44	0.15	−0.05	0.32	0.43	−0.03	**0.60**	**0.63**	0.22	1												
Public HI	−0.44	0.45	0.53	0.50	0.04	**0.70**	**0.74**	0.28	0.54	**0.63**	−0.52	**0.79**	0.56	0.37	0.46	1											
Freq. noise disrupt	0.23	0.11	0.54	0.52	0.13	0.39	0.34	−0.06	0.24	0.30	0.22	0.33	0.23	0.25	0.24	0.39	1										
Traffic noise	0.45	−0.19	0.14	0.18	0.10	−0.02	−0.11	−0.20	−0.01	−0.09	0.45	0.05	−0.03	−0.04	0.17	0.01	**0.73**	1									
Neighbor noise	−0.16	0.50	0.47	0.26	−0.06	0.56	0.53	0.36	0.47	0.51	−0.31	0.41	0.41	0.26	0.18	0.52	0.42	0.01	1								
Delayed rent	−0.37	**0.67**	**0.65**	0.52	**0.07**	**0.82**	**0.65**	0.28	**0.65**	**0.81**	−0.54	0.53	**0.62**	0.56	0.44	**0.67**	0.13	−0.32	**0.64**	1							
Food Stamp	−0.27	**0.66**	**0.82**	**0.75**	0.10	**0.84**	**0.92**	0.14	**0.70**	**0.74**	−0.38	0.46	0.36	0.40	0.26	**0.85**	0.42	−0.02	0.52	**0.70**	1						
% < High School	−0.25	0.31	0.49	0.49	0.14	**0.66**	0.52	0.04	0.52	**0.61**	−0.28	**0.83**	0.55	0.49	0.55	**0.80**	0.36	0.04	0.31	**0.63**	**0.62**	1					
% Unemployed	0.20	0.39	0.52	0.48	0.3	**0.77**	0.36	0	0.35	0.42	0.04	0.28	0.41	0.46	0.44	0.21	0.40	0.08	0.33	0.42	0.31	0.46	1				
% Poverty	−0.08	0.51	**0.64**	**0.60**	−0.03	**0.75**	**0.78**	0.19	**0.65**	**0.75**	−0.40	**0.79**	0.57	0.42	0.52	**0.92**	0.57	0.18	0.55	**0.63**	**0.89**	**0.80**	0.28	1			
% Non-White	−0.34	**0.64**	**0.62**	0.58	−0.01	**0.79**	**0.71**	0.10	0.50	**0.72**	−0.52	0.37	0.50	0.59	0.44	**0.70**	0.20	0.14	0.30	**0.77**	**0.73**	**0.60**	0.36	0.55	1		
% African American	−0.21	**0.72**	0.55	0.52	−0.02	0.59	0.48	0.15	0.51	0.49	−0.35	0.08	0.17	0.48	0.02	0.24	0	0.25	0.30	**0.63**	0.49	0.11	0.32	0.16	**0.70**	1	
% Hispanic	−0.25	0.14	0.40	0.35	−0.10	0.59	**0.63**	0.01	0.27	**0.63**	−0.32	**0.60**	0.49	0.39	0.55	**0.70**	0.34	0.06	0.23	0.47	**0.64**	0.76	0.20	**0.61**	0.57	−0.06	1

Bold values indicate Pearson rho ≥ 0.6.

EFA suggested a three-factor solution summarizing the inter-relationships among social stressor indicators (Figure 11). These three factors explained 92.7% of overall spatial variance across 26 social stressor indicators, and each exhibited distinct spatial patterning (Figure 12, next page). Factor 1 ('violent crime and physical disorder') included indicators related to violent crime, perceived lack of safety, unclean sidewalks, housing violations, and low area-level SEP (i.e., delayed rent/mortgage payments, Food Stamps enrollment, unemployment, proportion non-white and African American population). Factor 2 ('crowding and poor access to resources') included indicators related to residential crowding, poor access to healthcare resources, and other area-level SEP indicators (i.e., low educational attainment, high proportion Hispanic population). Factor 3 ('noise complaints and property crime') included indicators related to noise and air pollution complaints, mental health treatment, and property crimes, but not SEP. These factors explained 38%, 35% and 28% of variance, respectively, and were robust to sensitivity analyses.

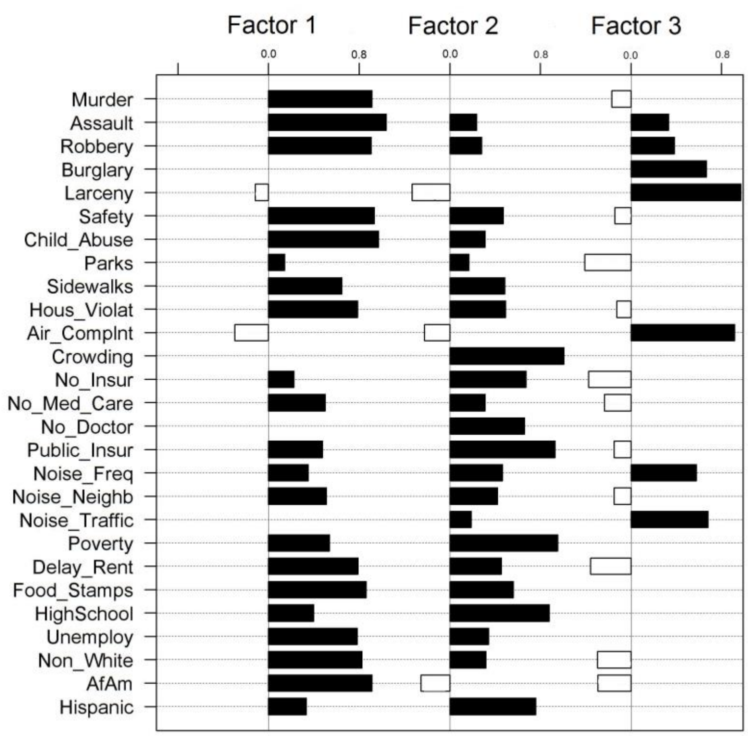


Figure 11. Factor Analysis 3-factor solution loadings

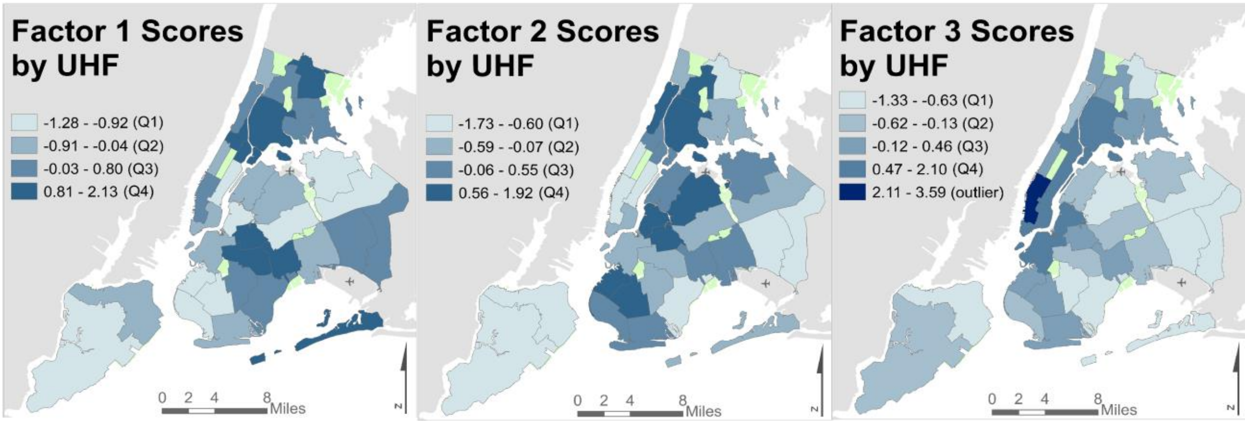


Figure 12. Maps of stressor factor scores, by UHF

To examine whether the geographically distinct patterns of social stressors represented by the three-factor solution provide different, or more comprehensive, information about the distribution of stressor exposures than simply considering any single indicator of area-level SEP, we assessed two commonly-used SEP indicators – area-level poverty (% households below 200% FPL) and low educational attainment (% adults with less than High School education) – across communities in the highest quartile for each of the three stressor factors. Among UHF areas with scores in the highest quartile for Factor 1, the mean poverty rate was 50%; for Factor 2, 53%; and for Factor 3, 41%; compared to the city-wide mean of 37%. Similarly, across UHFs with factor scores in the highest quartile, % less than High School education was above the city-wide mean (13%) for all factors (19%, 24%, and 15%, respectively).

3.2.2 Correlations between social stressors and air pollution

UHF-average concentrations of BC, NO_2, $PM_{2.5}$, and SO_2 were all positively correlated (rho = 0.74 to 0.96), and each inversely correlated with O_3 (rho = -0.69 to -0.90). We identified strong spatial correlations with pollutants [BC, NO_2, $PM_{2.5}$, and O_3 (inverse)] only for Factor 3 ('noise complaints and property crime’) (rho > 0.70) (Table 8). Factors 1 and 2 were not correlated with air pollution (rho = -0.07 to 0.08, and 0.04 to 0.12, respectively). Nor were poverty or educational attainment rates highly correlated with pollutant concentrations (rho = 0.01 to 0.17, and 0.01 to 0.11, respectively).

Table 8. Spatial correlation (Pearson rho) between stressor factors and air pollution, by UHF

	BC	NO_2	$PM_{2.5}$	SO_2	O_3
Factor 1 (violent crime and physical disorder)	-0.02	-0.01	-0.07	0.08	-0.01
Factor 2 (crowding and poor access to resources)	0.12	0.04	0.06	0.11	0.08
Factor 3 (noise complaints and property crime)	0.80**	0.83**	0.83**	0.44*	-0.74**

* indicates statistical significance at $p < 0.01$, ** $p < 0.0001$

3.2.3 Stressor factors and NO2 on child asthma ED visits

Citywide, during 2008-2010, the mean UHF-level rate of child (0-14 years old) asthma-related ED visits was 6.8%. Mean annual NO_2 concentrations across UHF areas ranged from 15.7 to 39.3 ppb (mean 25.1 ppb). In separate ecologic regression models for each stressor factor and NO_2, on asthma ED visits, we found a significant association only for Factor 1 (‘violent crime and physical disorder’); an IQR increase in Factor 1 was associated with a 3.9% increase in childhood ED visits ($p < 0.0001$). No associations were evident for other factors, or for area-average NO_2. The association for Factor 1 remained after adjusting for Factors 2 and 3, and NO_2.

We examined effect modification in the NO_2-asthma exacerbation relationship by stressor factors (Figure 13, next page), and found significant ($p < 0.05$) modification only by Factor 2 (‘crowding and poor access to resources’); among UHF areas scoring above the median on Factor 2, each 10 ppb increase in area average NO_2 was associated with a 5.5% increase in child asthma ED visit rates. Given potential outcome bias for Factor 2 (which included access to health care indicators), we sensitivity-tested this effect using single health care access indicators, finding no significant modification.

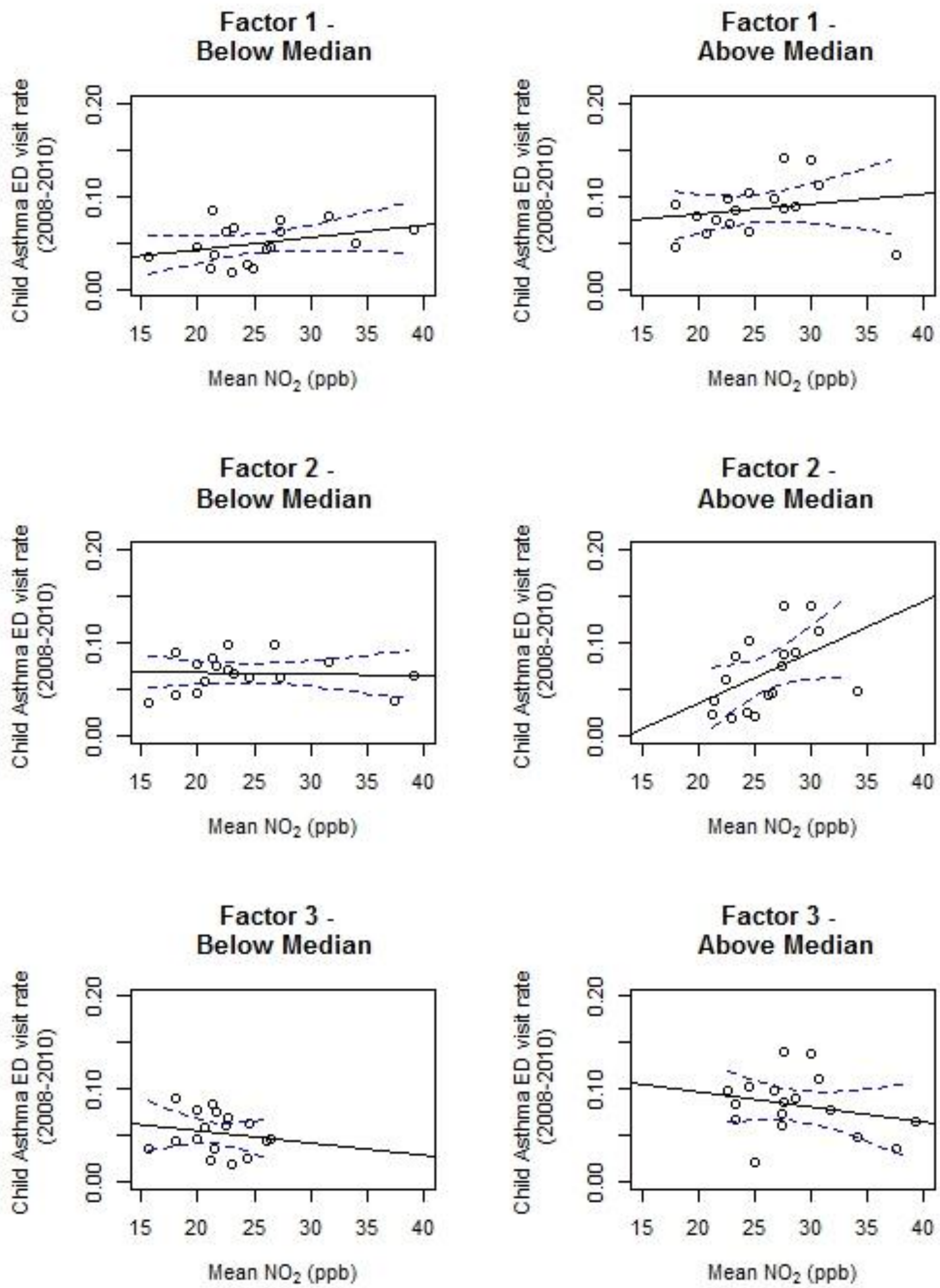


Figure 13. Modification of the association between area-level NO_2 and child asthma ED visit rates, by social stressor factors

We compared these model results to those using area-level poverty rates (Table 6, page 49) as the modifier. The association between poverty rates and ED visits was slightly weaker than the association observed for Factor 1 – an IQR increase in % households below 200% FPL conferred a 2.3% increase in ED visits – with a substantially weaker model fit (R^2 = 0.24 vs. 0.54). We found no modification of the association between NO_2 and asthma ED visits by area-level poverty rates.

3.2.4 Sensitivity Analyses

To evaluate the sensitivity of correlations among stressor indicators to the unit of aggregation [Modifiable Areal Unit Problem (MAUP) (Openshaw 1984)], we aggregated two high-resolution spatial data sets (NYCCAS smooth surface air pollutants, and census tract variables) to each administrative unit. Correlations were consistent across units, supporting the reliability of our findings (Table 9). We also tested the sensitivity of autocorrelation detection to the spatial weighting method (i.e., first-order contiguous neighbors versus inverse distance between area centroids) and unit of aggregation, which did not influence results.

Table 9. Unit of aggregation (MAUP) effects on correlation measures (Pearson rho) between multiple pollutants and census variables, aggregated to three different administrative units

	CD (n=59)			PP (n=74)			UHF (n=34)		
	% < 200% FPL	% Unemp.	% Non-White	% < 200% FPL	% Unemp.	% Non-White	% < 200% FPL	% Unemp.	% Non-White
$PM_{2.5}$	0.01	0.04	-0.16	-0.19	-0.05	-0.27	0.08	-0.02	-0.21
EC	0.13	0.17	-0.01	-0.11	0.01	-0.20	0.14	0.07	-0.10
NO_2	0.02	0.02	-0.11	-0.18	-0.08	-0.23	0.10	0.00	-0.14
SO_2	0.24	0.33	0.10	0.18	0.25	0.03	0.20	0.29	0.03
O_3	-0.02	-0.09	0.01	0.32	0.25	0.32	-0.01	-0.02	0.07

3.3 DISCUSSION

We used GIS-based techniques to quantify relationships across social stressor indicators, and between these potential social stressors and air pollutants across NYC. Our findings call attention to complex spatial patterning across diverse stressors and SEP, and emphasize the importance of refined social exposure assessment for environmental health research. This spatial approach enables the disentangling of potentially correlated, yet conceptually distinct, chemical and non-chemical exposures – towards better quantifying spatial confounding and effect modification in social-environmental epidemiology.

Importantly, we found that a diverse set of social stressors across NYC are: 1) not consistently correlated, even among indicators that appear to be measuring similar aspects of the social environment (e.g., crime indicators), 2) not consistently correlated with area-level SEP, and 3) not consistently correlated with air pollution. The complexity of relationships among stressor indicators was borne out in factor analysis, which identified three spatially-distinct suites of stressors – 'Violent crime and physical disorder,' 'Crowding and poor access to resources,' and 'Noise complaints and property crime' – suggesting that co-variation might be driven more by common spatial patterning than by shared meaning. Importantly, these three spatial factors did not represent different levels of socioeconomic position; areas that were similar with respect to SEP indicators did not necessarily have similar prevalence and combinations of other social stressors. As such, using any single stressor (including SEP) measure to serve as a proxy for psychosocial stress may be misleading; because areas that may be similar with respect to area-level SEP measures may differ regarding social stressors, single measures may inadvertently lead to confounding, and fail to capture important nuances of the social environment. It is also worth noting that some communities had high factor scores for more than one stressor factor, underscoring the potential for cumulative effects of multiple exposures in those communities. While the spatial patterning empirically summarized by stressor factors would likely differ between cities and regions, this reproducible approach may be helpful in developing locally appropriate composite social stressor measures.

Leveraging common spatial patterns among social stressors across communities enabled a more comprehensive characterization of social exposures, and perhaps psychosocial stress, and potential interactions with air pollution, which may contribute to social disparities in health. For example, in our ecologic analysis, air pollution was strongly correlated only with the spatial factor corresponding to 'Noise complaints and property crime' (Factor 3), not with the other factors, or with indicators of SEP. This is noteworthy, as communities with relatively high SEP and better healthcare access loaded relatively strongly on Factor 3 – a result which counters the common assumptions that air pollution would be highest in low-SEP communities, leading to positive confounding in air pollution epidemiology. It is also of note that our only indicator of perceived pollution – air quality complaint rates – loaded strongly on Factor 3, suggesting correlation between spatial patterns in modeled pollution concentrations and perceived air poor quality. The ability of pollution (or its sources) to act as both a chemical and non-chemical stressor is increasingly recognized as an important source of confounding (Clougherty et al 2014).

In our ecologic analysis, we illustrated how modification in the NO_2-asthma exacerbation association may vary substantively by the selection of social stressors – represented here by our three stressor factors. Conceptually, this ecologic analysis underscores the need for thoughtful selection of stressor indicators, as mis-specification of stressors, which are hypothesized to impart physiologic susceptibility, can substantially alter observed effect modification. Further, empirically grouping social stressors according to spatial relationships (i.e., factor analysis) may better capture potential physiologic susceptibility patterns, relative to using a single stressor indicator – an observation which is reinforced by our result that area-level SEP indicators did not strongly correlate with stressor factors, and thus are likely inadequate proxies for stressor exposures and psychosocial stress.

Though there are few examples in environmental epidemiology for refined social exposure assessment, our findings recall notions of "unpatterned inequality" in urban resource distribution, wherein communities may be favored in the allocation of some resources, while deprived in others (Lineberry 1975). In a recent study of area-level associations between SEP and air pollution, Hajat et al. (2013) identified regional and intra-urban heterogeneity in the strength and direction of associations between area-level SEP and air pollution using spatially-informed regression models, wherein SEP was positively associated with $PM_{2.5}$ and NO_X exposures across a geographic subset of NYC communities. More work is necessary, however, to replicate and refine salient social stressor measures, especially for large geographic cohorts wherein individual-level survey assessments of stress experience [e.g., (Hicken et al. 2013)] or on-foot built environment assessments [e.g., (Kroeger et al. 2012)] are generally infeasible.

3.3.1 Limitations

An alternative explanation for our empirically-derived findings include spurious associations due to unit of analysis (i.e., administrative areas are highly imperfect proxies for communities), measurement error in administrative data, or construct misspecification. Generally, larger administrative areas yield less precise metrics (Maantay 2002); thus, while we aimed to include the widest variety of administrative indicators of social stressors possible, each indicator was examined at the finest resolution available, and areal units were robust to MAUP effects. Likewise, some stressor indicators may capture aspects of both chemical and non-chemical exposure constructs. For example, some physical disorder indicators are linked with poor mental health, but also with allergen and chemical exposures (e.g., cockroaches, pesticides) – both implicated in asthma etiology. Here, we attempted to minimize such confounding by focusing on stressors hypothesized to act predominantly through psychosocial stress pathways. These interpretation challenges are not, however, unique to this analysis, as administrative indicators are widely employed in social and environmental epidemiology. As such, mixed qualitative and quantitative methods for identifying salient stressors across spatially heterogeneous domains, and for validating administrative indicators against community- and individual-level stress experience (e.g., Schulz et al. 2008), are promising approaches for improving reliability of administrative indicators for environmental epidemiology.

3.3.2 Strengths

We aimed to develop and validate broadly applicable methods for quantifying common spatial patterning across urban chemical and non-chemical exposures. The NYCCAS fine-scale air pollution data enabled examination of spatial correlations across pollutants – and between pollution and social stressors – and provided fine-scale surfaces for validation of areal re-aggregations. GIS-based sensitivity analyses lend confidence to our quantitative findings. First, our validation method for areal weighting of incongruent spatial units could utilize any smooth surface supplying a known underlying distribution (e.g., elevation raster, kernel density surface), ideally with a scale of variability similar to (or more refined than) the re-aggregated exposure of interest. Though areal reformulation may induce local exposure misclassification, due to unknown within-area variability, our approach is useful in identifying global spatial confounding patterns. Second, sensitivity testing for MAUP effects and autocorrelation improved our understanding of spatial correlations, providing insights for future spatially-informed multi-variable modeling of social-environmental interactions.

3.4 CONCLUSION

Our city-wide examination of social stressors and air pollution in one U.S. city highlight the utility of spatial analysis for disentangling the separate and combined effects of chemical and non-chemical exposures. The process presented for systematically identifying and assimilating area-based administrative indicators of social stressors, and deriving empirical spatially-covariant composites can minimize confounding among social stressors, and between social stressors and air pollution. Our findings demonstrate that selection of social stressors may substantially alter observed effect modification, caution against using single SEP indicators as proxies for social stressors, and demonstrate the risks associated with mis-specification of social stressor exposures. Empirical studies with stronger validated and spatially-informed measures of social stressor exposures are needed to better understand spatial confounding and joint effects between chemical and non-chemical stressors.

4.0 IDENTIFYING PERCEIVED NEIGHBORHOOD STRESSORS ACROSS DIVERSE COMMUNITIES IN NEW YORK CITY

Growing interest in the role of social stressors in health disparities (Gee and Payne-Sturges 2004; Morello-Frosch and Shenassa 2006; Nweke et al. 2011) and cumulative risk assessment (EPA 2003; Sexton and Linder 2011; McEwen and Tucker 2011; Lewis et al. 2011) is particularly important for communities burdened by multiple social and environmental risk factors. Improved methods are needed, however, to identify which social stressors are most important to urban community residents, towards accurately incorporating neighborhood stressors into public health research, developing effective interventions, and ultimately elucidating psychosocial pathways for health effects. To this end, we developed and implemented a community-engaged process for identifying and characterizing key perceived neighborhood stressors, through focus group discussions with diverse communities across NYC.

Adverse physiological alterations resulting from psychological stress can arise through a multi-stage stress process wherein an external stressor (event or condition) may overwhelm an individual's perceived capacity for coping (Cohen et al. 1995) – leading to both unhealthy behaviors and maladaptive biological processes. Because psychosocial stress, and thus its adverse physiologic impacts [i.e., allostatic load (McEwen and Seeman 1999)], are mediated through negative appraisal, precise assessment of stressor exposure levels needs to account for *perception*. Perceived stressors and their importance may differ across both individuals and communities. Qualitative research methods, such as focus groups, are well-suited for providing insight into community perceptions and priorities (Patton 1999; Payne-Sturges 2011). Previous qualitative studies examining perceptions of community stressors in NYC have largely focused on a single stressor domain, such as violence (Fullilove et al. 1998) or environmental hazards (Green et al. 2002), generating in-depth information about specific communities. Here, however, we aim to identify that range of neighborhood characteristics which are perceived as important stressors by residents across a range of NYC communities, and to understand the relationships among these stressors, towards informing our on-going study of potential interactions among multiple social and physical exposures. Such community-engaged research approaches can improve the quality, credibility, and relevance of research findings (Hacker 2013; Blazas and Morello-Frosch 2013), towards improving the accuracy of stressor assessment, and ultimately translating health research into practical interventions.

To identify and characterize perceived neighborhood stressors, and their relative importance, across NYC communities we implemented a multi-community study, consisting of semi-structured focus groups, ranking exercises, and systematic content analysis. Because of longstanding environmental justice (EJ) concerns about cumulative impacts of multiple exposures (Gee and Payne-Sturges 2004; IOM 1999), specifically in NYC (Maantay 2007; Corburn et al. 2006), we emphasized recruitment in potential EJ 'areas of concern,' based on demographic composition and/ or pollution source density (NYS DEP). Our main goal was to ask communities to tell us which neighborhood conditions they feel induce stress (and why) – we intentionally avoided focusing discussions around any stressors identified *a priori* – to elucidate residents' ideas of key stressors, towards refining locally-specific perceived stress survey instruments, and informing on key stressors to incorporate in our epidemiological study. We hypothesized that community discussions would encompass a broad range of neighborhood stressors, and we aimed to engage discussion around both social and physical neighborhood characteristics. Here, we synthesize the information we collected on perceived stressors across NYC communities, and discuss the potential implications of this work for understanding psychosocial stress and cumulative impacts in public health research.

4.1 METHODS

4.1.1 Recruitment and Study Participants

To facilitate recruitment from multiple NYC neighborhoods, research team members from WE ACT for Environmental Justice (WE ACT) – a non-profit environmental justice organization in Harlem, NYC – engaged numerous community-based organizations (CBOs) working in disadvantaged communities and EJ areas of concern, on issues of environmental health, youth engagement, and economic development. WE ACT worked with CBOs to recruit local residents by distributing flyers and attending CBO meetings. Recruitment flyers stated our overall research aim of understanding social stressors and susceptibility to air pollution in childhood asthma. We aimed to recruit for three focus groups in each borough (n = 5) – including at least one English- and one Spanish-language, and one adolescent (English) group in each borough – for a total of 15 groups. For eligibility, we required only that adults be neighborhood residents, and adolescents also needed guardian consent. Focus groups were conducted at CBOs across NYC, and participants were assigned to focus groups based on residential proximity. Participants received $20 as an incentive.

Table 10. Focus group participants' self-report demographic composition

Adult Focus Groups	**Median**	**Range**
Number of participants	10	6 - 17
Gender (% Female)	83%	45% - 89%
Race / Ethnicity (% African American and/or Hispanic)	90%	70%-100%
Age	47	18 - 83
Household income (in multiples of the Federal Poverty Line (FPL))	<1x FPL	<1x - 7x FPL
Neighborhood residential tenure	5 - 10 years	1 - 5 - >10 years
Educational attainment	Some college	<5th grade - Graduate degree
Youth Focus Groups	**Median**	**Range**
Number of participants	7	7-12
Gender (% Female)	43%	25% - 71%
Race / Ethnicity (% African American and/or Hispanic)	85%	60% - 100%
Age	16	14 - 20
Household income (in multiples of the FPL)	1 - 2x FPL	<1x - 3x FPL
Neighborhood residential tenure	5 - 10 years	<1 - >10 years
Educational attainment	Some high school (HS)	Some HS - Some college

The majority of focus group participants self-identified African American and/ or of Latino ethnicity (Table 10). Spanish- and English-language groups were demographically similar, except that Spanish-speaking participants reported slightly lower educational attainment, on average. The majority of participants resided in the neighborhood, or in a neighborhood adjacent to where the focus group was conducted, and most reported a residential tenure of five to ten years. Some participants knew each other previously – through involvement in the CBO, and/ or neighborhood or school networks.

Though most participant communities fit the NY State Department of Environmental Conservation criteria for EJ areas of concern, they varied substantially in prevalence of neighborhood stressors (e.g., crime rates, poverty), as measured by administrative aggregate data. Figure 14 (next page) illustrates the spatial distribution of focus group locations, and

Community Districts corresponding to participants' self-reported residential neighborhoods, which include roughly half of NYC administrative areas.

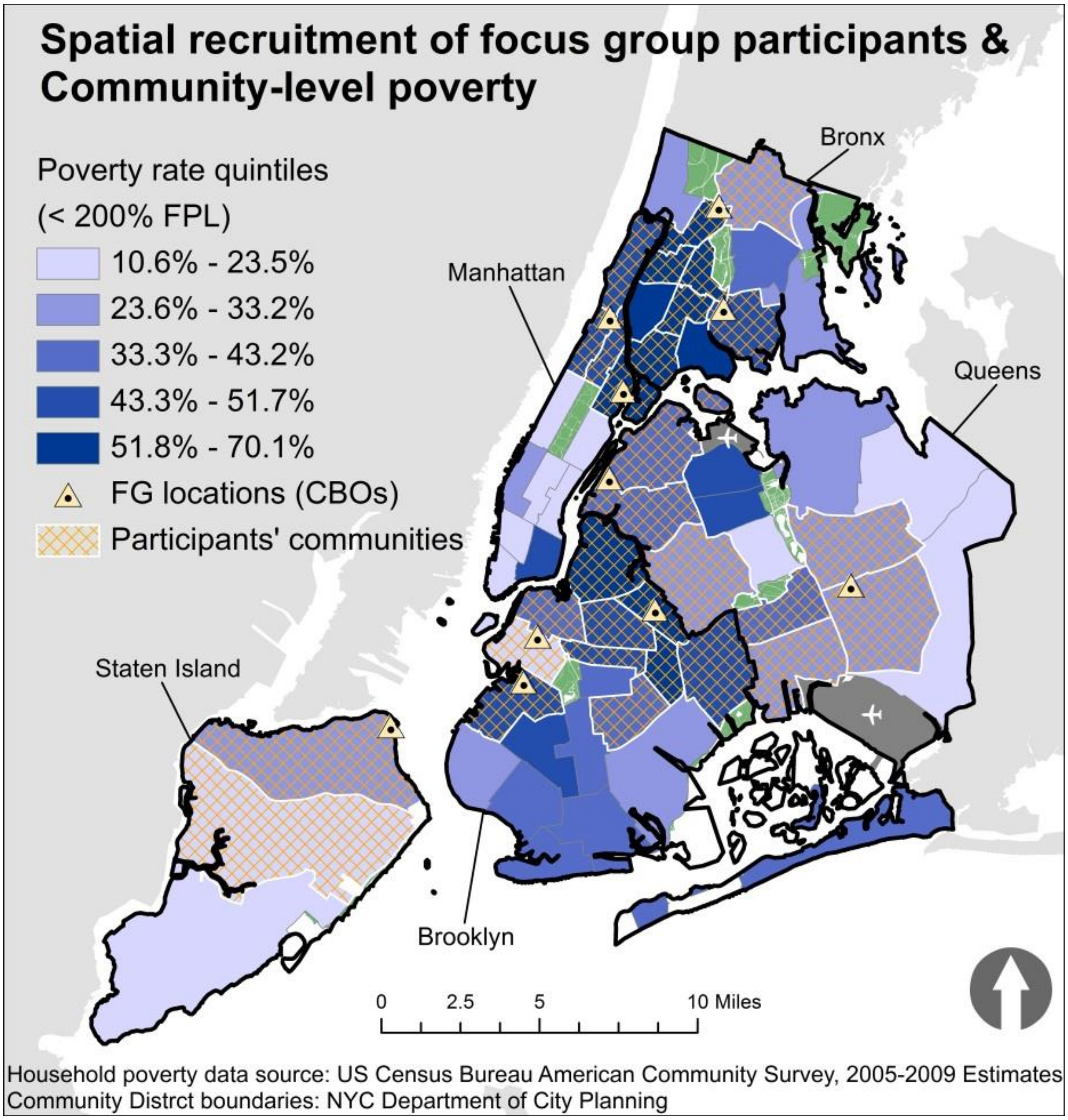
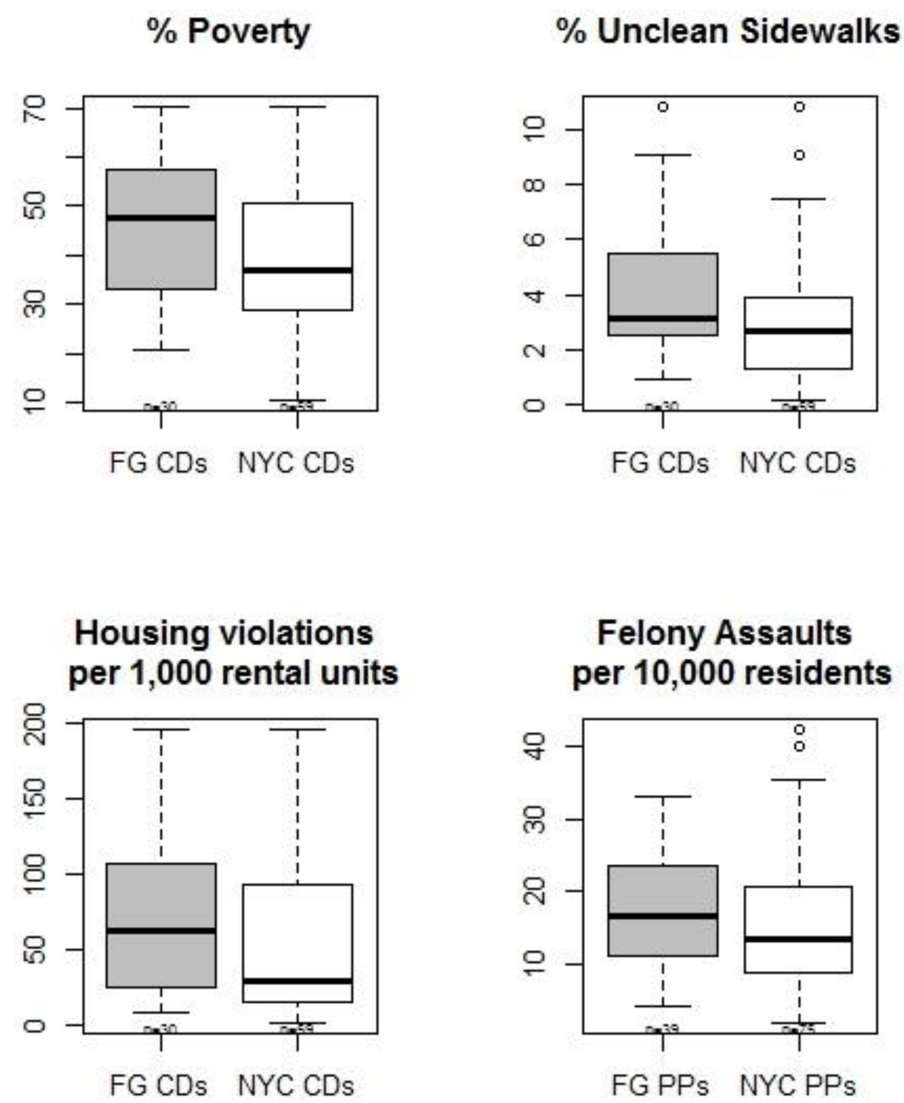


Figure 14. Spatial distribution of focus group locations and participants' communities

Figure 15 compares prevalence of four administrative indicators of social stressors - % below 200% FPL, % unclean sidewalks, serious housing violations among occupied rental units, and felony assault rates – across focus group participants' communities, versus across the entire city.



Data sources (clockwise, from % Poverty): American Community Survey (2005-2009); NYC Mayor's Office of Operations (FY2009); NYC Department of Housing Preservation and Development (2009); NYPD (FY2009).

Figure 15. Administrative indicators of stressor prevalence across focus group communities, versus NYC

4.1.2 Data Collection

From May to October 2012, we conducted 14 focus groups: nine adult and five adolescent groups (ages 15-19), consisting of 6-13 participants (median = 9), and ranging from 45-89% female composition (median = 83%). Semi-structured discussions were facilitated by two WE ACT team members (moderator and note-taker), and informed consent was obtained from all participants (and guardians of minors) prior to initiating any study procedures.

Discussing perceptions of social stressors can be sensitive, and we aimed to facilitate an open and safe discussion format to encourage maximum participation, and to generate high-quality data. For consistent facilitation, we developed a moderator's guide, consisting of: 1) introduction of the study and disclosures (e.g., audio recording), 2) semi-structured discussion of neighborhood characteristics, and 3) interactive ranking. See Appendix C for full moderator's guide. Discussions lasted approximately one hour.

Experienced moderators (WE ACT) first asked participants to discuss their perceptions of neighborhood geography (i.e., "*How do you define the edges of your neighborhood?")* to build rapport and get participants thinking about their community. Moderators then asked participants to describe positive, followed by negative, neighborhood attributes, and listed all attributes on poster-paper. Both positive and negative neighborhood attributes could be listed. Moderators prompted participants to distinguish between 'physical' and 'social' characteristics, in keeping with stress process theory on differing domains of chronic stressors (Aneshensel 1992). Discussions continued until no new neighborhood attributes were identified (i.e., saturation). Table 11 (next page) lists neighborhood stressors named by participants, ordered by the number of groups in which the attribute was discussed.

Table 11. Neighborhood stressors identified by participants

Community-identified Stressors	# of groups
Safety (violence, crime)	14
Drugs (dealers, use)	9
Sanitation (trash, rats, pests)	9
Police presence (Stop-and-Frisk)	9
Public transportation	7
Lack of involvement from city officials	6
Gang activity	6
Gentrification	6
Lack of community pride, unity, involvement	6
Poor housing conditions, inadequate housing	6
Disrespect, harassment among community members	5
Diminishing services, funding cuts	5
Traffic	4
Noise, raised voices, loud music	4
High cost of living	4
Lack of emergency services, hospitals	3
Sexual assaults	3
Schools	3
Prostitution	2
Construction	2
Guns	2
Pollution	2
Lack of grocery stores	2

Moderators used an interactive ranking exercise known as "dot democracy" to assess the relative importance of listed stressors. First, participants revisited the list of negative neighborhood attributes, toward clarifying nuanced, and sometimes conflicting, perceptions. Then participants placed two sets of 'dot' stickers on the list to: 1) corroborate which neighborhood attributes they found stressful, and 2) indicate what they (each individual) thought was the "most important" stressor.

4.1.3 Data Analysis

Focus group audio recordings were transcribed verbatim, and English translations of Spanish-language transcripts were reviewed by a native Spanish speaker at WE ACT who found good agreement, thus transcripts were not back-translated. We employed an iterative coding process, following constant comparative method, moving from statement-to-statement to statement-to-whole comparisons, followed by thematic synthesis (Glaser 1965). Two analysts (GSPH) reviewed each audio recording and transcript multiple times, noting variations in speakers' tone or intensity, before coding. Analysts followed consistent coding protocols (e.g., coding complete quotation blocks (to preserve context), applying multiple codes), using ATLAS.ti v6 content analysis software (Scientific Software Development 1997). We generated an initial set of codes based upon neighborhood attributes listed by participants, and debriefing conversations with WE ACT facilitators. We then developed a hierarchical coding dictionary, in which attributes could be coded as 'social' or 'physical,' and 'positive' or negative.'

To ensure inter-coder reliability, analysts independently coded a subset of three randomly-chosen transcripts – one youth, one Spanish-language (translated) adult, and one English-language adult group, each from a different borough – and calculated a kappa score to quantify agreement between coders (Landis and Koch 1977), using open-access Coding Analysis Toolkit (UCSUR). Finding an inter-coder reliability score of 0.71, indicating "substantial agreement" (Viera and Garrett 2005), the remaining transcripts were coded individually. Discussion quotations were sorted by code, with identifiers for group-type (e.g., adolescent, adult) and co-occurring codes, and discussed amongst analysts and facilitators.

Thematic summaries of prominent stressors, and then over-arching themes, were developed by study investigators (GSPH) and discussed and confirmed with community research partners/moderators (WE ACT), toward synthesizing and reaching consensus around connections between participants' perceptions. We referred to aggregate dot democracy rankings of important neighborhood stressors to provide methods triangulation with content analysis.

All study procedures were approved by the University of Pittsburgh Institutional Review Board and the Western Institutional Review Board (WE ACT), which independently approved the study protocol.

4.2 RESULTS - NEIGHBORHOOD STRESSOR THEMES

We found substantial overlap across groups in the neighborhood stressors listed, and consistency in those stressors ranked as 'most important.' We identified nine prominent neighborhood stressors: gentrification, police presence, housing, sanitation, safety/gangs, discrimination, housing, parks, and schools (youth only). Three overarching themes characterized the stressors commonly identified and discussed: (1) police and safety, (2) physical disorder and neglect, and (3) gentrification and racism. In the following sections, we detail the comments and experiences participants reported on each of these themes.

4.2.1 Police and Safety

Participants across ages and boroughs shared conflicted feelings about the police presence in their neighborhoods; while adults in particular attributed a decrease in criminal activity to increased police presence (e.g., foot patrols, surveillance cameras), participants put more emphasis on the associated stress of police harassment and racial profiling (i.e., Stop-and-Frisk policy). One youth participant described these conflicted perceptions of police by stating that *"It's good because it provides protection to the citizens, but it's bad because it kind of like, I don't know, it just makes me feel uneasy because you have the cops just like roaming around the* *neighborhood. They might abuse it."* Having more police patrolling in neighborhoods was described as stressful because of the perception that police were apt to "*vent*" anger on residents. In the words of another young person: "*Cops are like the stress where it's like, you know, you're trying to just mind your business, and then like the cops just bother you, that's what makes it stressful that you can't really mind your business."* Some adult participants described police as not caring about, respecting, or wanting to be in the communities in which they work, and others had harsher words: *"You can't, these days you can't say nothing to them. Come on, you got to be mindful. I mean, come on. They are shooting our boys – our young men down like, like they are animals."*

While neighborhood safety and police presence were perceived to be related, participants differentiated seeing police and feeling protected. Discussions about safety focused on gun violence and gangs, but also noted a rise in sexual assaults. Participants discussed feeling unsafe outdoors, especially at night, as one young person described: *"I don't feel well protected in my neighborhood. At least, I can't go out at night like adults could when they were young. Young people today have to go out early in the morning and come home before it gets dark because if you don't something is going to happen, or your parents will be very worried.*" Participants talked about avoiding unsafe areas in their neighborhoods. Specifically, parks were widely associated with violence and drug use, as highlighted in one adult participant's comment: *"I won't consider going to parks now…. You go and you wonder what's going to happen… Everything could be so nice and quiet and then all of a sudden, 'Boom,' you run for your life."*

4.2.2 Physical Disorder and Neglect

Neither adult nor youth participants readily distinguished physical and social domains of neighborhood stressors. Physical neighborhood stressors – including sanitation, housing quality, parks, noise, and traffic – were overwhelmingly described as representing neglect, disrespect, or lack of community accountability. Cleanliness and sanitation were identified as important problems, and were discussed as indicative of neighbors' disregard for each other. Parks were broadly viewed as being neglected and lost opportunities for something nice in the community, as expressed by one adult participant, "*You can't even go to the park and be calm because they're smoking marijuana and all of that in front of the children. It's of lack of respect for children."* Some participants tied this lack of respect to a *"reduction in community pride,"* as one adult participant noted that *"One thing that keeps a community going, whether there's money, whether there's jobs, whether there's good times or bad times, is that people were really proud of where they live."*

Adult and youth participants discussed the quality of their physical environment relative to other neighborhoods, specifically that more affluent neighborhoods were perceived as better taken care of, whether due to resident or agency actions (e.g., cleaning subway stations). For example, one adult participant stated that "*as people living in the community we should be keeping our place clean and sacred. Instead we – and I've seen it with my own eyes – eat something and leave. You go to Manhattan and you see how those streets are,"* referencing Manhattan as a more affluent area. Likewise, adult and youth participants perceived landlords in more affluent areas as more responsive to making repairs and investments in their buildings.

References to pollution sources and chemical exposures were rare, compared to other aspects of the physical environment, and were not ranked among "most important" stressors in any group that discussed pollution or its sources. Vehicle traffic, for example, was described by participants in multiple groups as negative because of perceived driver carelessness and risks to pedestrians, not as a source of air pollution. Two groups discussed a local industrial facility, and participants in one group directly connected facility emissions with elevated child asthma rates.

4.2.3 Gentrification and Racism

Adult and youth participants alike discussed potential community benefits of gentrification (e.g., new businesses, increased governmental attention to public safety), but more often referenced negative effects on long-term residents, and particularly on residents of color. Participants expressed sadness and loss due to gentrification, as highlighted by one young person's statement that "*gentrification is the reason why I don't consider one of my places in Harlem my community anymore.*" Rising rents were frequently tied to stress, along with frustration with neglectful landlords, and feelings of powerlessness among tenants. Incoming residents were perceived by both adult and youth participants as lacking respect for long-term neighborhood residents, and being more likely to stereotype them.

Perceived mechanisms of gentrification included rising rents, lack of home-ownership among African-Americans, and alignment of politicians with real-estate developers. One adult participant shared the perspective that assets can make communities targets for gentrification: *"We got excellent transportation. That's why they want us out of here… They really think they're entitled to it all."* Construction and residential re-development were associated with loss of historic and cultural assets (e.g., schools, hospitals), and many participants discussed "*forcing out*" residents along racial lines, and "*shifting populations*" through the "*taking of physical* *structures, like hospitals and schools and making them into condominiums, upper-scale residential sites…"*

Adult and youth participants discussed unfair treatment of individuals and communities of color by authorities (e.g., politicians, police) across a range of domains (e.g., housing, schools, sanitation). Perceived racial preference for white, upper-class "*outsiders*" by businesses were viewed as directly related to neighborhood gentrification, and participants broadly perceived landlords as discriminating against long-term residents, particularly Hispanic immigrants. One adult participant stated that:

> *The government people - the landlords take advantage of Hispanics because there are a lot of things that need repair in the building and they don't fix it. And there isn't any government protection to ensure that the landlords do it. Many times we are too afraid to say anything because we think we may get thrown out and they don't fix anything.*

4.2.4 Youth Perceptions of School Environments

While adults and youths similarly characterized neighborhood stressors, concerns about the school environment were unique to youth participants. Young people described school as stressful, specifically yelling by students and teachers, waking up early, keeping up with work, exams, fitting in, and safety. One young person stated:

> *School is stressful 'cause, like, you know, people drop out, you know, the stress eats at people, like not just high school and junior high, but like college… It's just stressful, like you got to stay on a regimen, you got to do all your homework, you got to make sure that you don't stick out from a crowd, like you're not intelligent enough to be in a class.*

Youths described prevalent favoritism by teachers and the perception that some kids *"always get passed."*

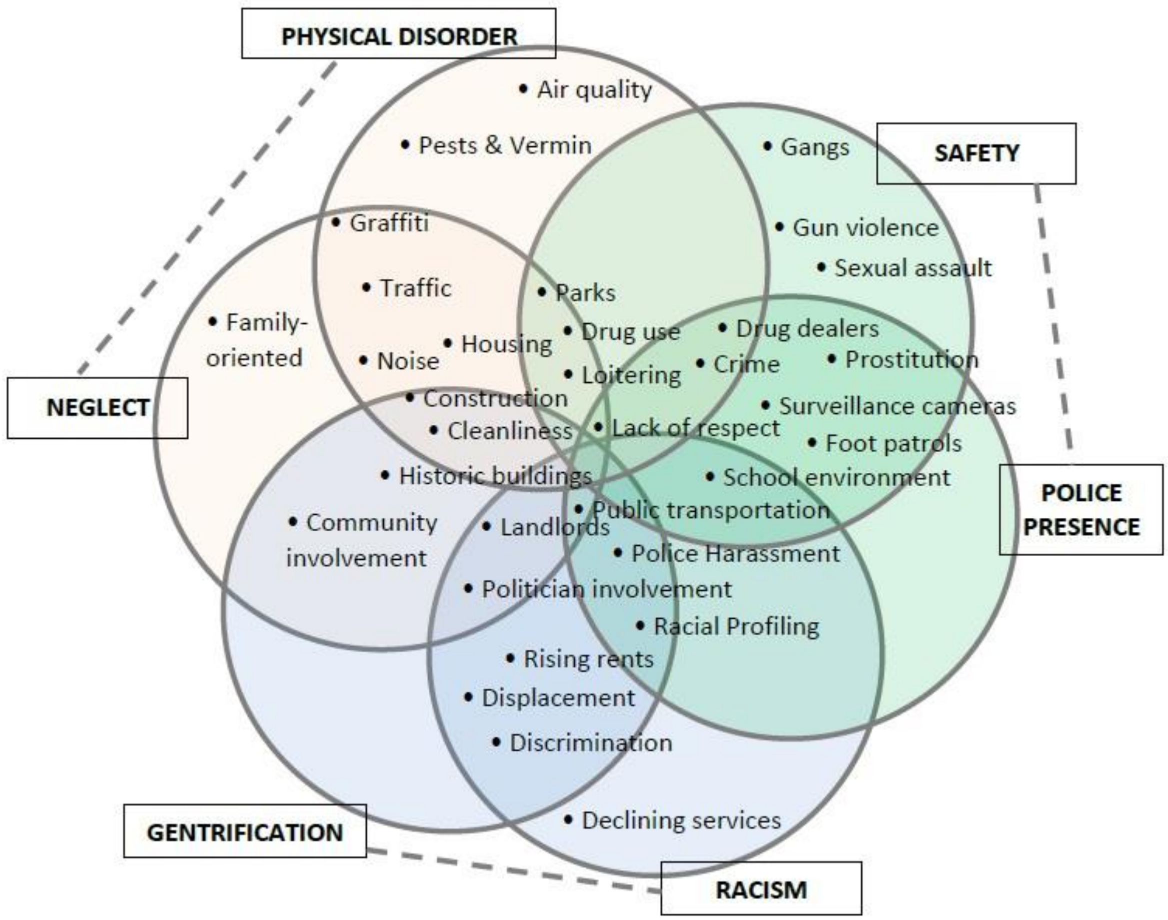


Figure 16. Inter-relations among perceived stressor themes and neighborhood attributes

We note that while these stressor themes emerged consistently across discussion groups, they were not described as discrete topics, but rather as inter-connected issues. For example, distress related to racial profiling was discussed most commonly in the context of increasing police presence and perceived lack of safety, but some participants also described a rise in police profiling and harassment associated with gentrification. In Figure 16, we use a Venn diagram to represent perceived inter-relations among neighborhood attributes, as revealed through participant discussions and systematic content analysis.

4.2.5 Dissemination of results

To communicate study findings to community residents, we developed a lay poster describing the study and neighborhood stressors themes identified through focus group discussions (see Appendix D), which was distributed to the CBOs who participated in recruitment and hosted focus groups.

4.3 DISCUSSION

A nuanced understanding of perceived neighborhood stressors is needed to help elucidate complex psychosocial pathways to ill health and susceptibility, and to understand potential synergies with chemical exposures. Community-engaged, qualitative research methods allowed us to capture local experiences and perceptions, towards refining survey instruments, study hypotheses, and ultimately will improve the accuracy of epidemiology attempting to understand complex exposure pathways among social and physical exposures. Using focus group discussions to document perceived neighborhood stressors across diverse urban communities, we identified inter-related stressor themes – police and safety, physical disorder and neglect, and gentrification and racism – and discuss here how our findings can inform emerging issues and approaches for social-environmental health research.

In our study, participant reports of navigating around perceived unsafe places as a protective strategy, as is consistent with previous qualitative research in low-income NYC communities of color (Fullilove et al. 1998; Green et al. 2002). In addition, our findings highlight the previously less documented role of community-police dynamics as a source of chronic stress. Specifically, police behaviors associated with the NYC Police Department (NYPD) Stop-and-Frisk crime reduction initiative, which broadly authorized officers to question and search citizens (NY State Criminal Procedure Law section 140.50), were identified as important stressors for the community at large. Many participants shared personal experiences and observations of abuse of police authority and racial profiling, rather than referencing news stories regarding high profile abuse cases, for example. Though a federal judge has since ruled that Stop-and-Frisk tactics violated the constitutional rights of racial minority populations in NYC, this work adds to the small but growing literature documenting the ways in which public policies, such as immigration enforcement (Hacker et al. 2011; Sabo et al. 2014), may inadvertently induce community distress. Given other research indicating that perceived lack of safety may be particularly important for mental (Aneshensel and Sucoff 1996; Wilson-Genderson et al. 2013) and respiratory health (Subramanian and Kennedy 2009; Vengeepuram et al. 2012), investigators interested in understanding the role of safety-related distress may benefit from also evaluating community-police dynamics from residents' perspectives.

Distinguishing effects of social and physical factors in the built environment and neighborhood settings is a longstanding challenge in health research (Schulz and Northridge 2004), as pathogenic (e.g., cockroach endotoxin, insecticide use) and social (e.g., poverty) exposures may co-occur. Despite the use of structured cues in the moderator's guide to facilitate discussion of social and physical neighborhood stressors, this distinction did not seem intuitive to participants. This could be an artifact of discussion facilitation, but may also reflect how intertwined these domains are with regard to how individuals experience perceived stress. For example, neighborhood attributes commonly used as indicators of ‘physical disorder’ in health research [e.g., sanitation, housing quality (Ross and Mirowsky 2001; Sampson and Morenoff 2004)] were described by study participants as representing community accountability – suggesting perhaps that social capital [i.e., norms of reciprocity, cooperation, and trust (Kawachi et al. 1997)] may be a potential buffer against stress-related effects of physical disorder. These findings also suggest that psychosocial pathways may be inadvertently captured in “objective” measures of the built environment [e.g., traffic volume (McGinn et al. 2007), housing dilapidation (Kroeger et al. 2012)], creating confounding between psychosocial and physical environmental pathways.

Though local pollution and its sources were not widely discussed, other studies have found evidence for stress effects across a range of perceived pollution exposures, including malodor (Horton et al. 2009), industrial chemicals (Couch and Coles 2011), and unconventional natural gas drilling emissions (Ferrar et al. 2013). This possibility for environmental pollution to act along both traditional (i.e., dermal, inhalation, ingestion) and psychosocial exposure pathways is another area of potential confounding, or synergism, particularly for EJ communities.

Mechanisms through which gentrification may impact health [e.g., distress due to social network disruptions, or rising housing costs (Murdie and Teixeira 2011) are not well understood, and are further complicated by its perceived potential to bring about both positive and negative neighborhood changes. In our study, while participants acknowledged both risks and benefits of gentrification, as in other studies (Formoso et al. 2010; Betancur 2011), adult and youth participants emphasized unfair treatment and displacement of long-term residents of color in this process. This emphasis on the inter-relation between gentrification and experiences of racism suggests that discrimination may be an important factor [generally negatively appraised (Williams 1999)] for understanding distress related to gentrification. Further, the perceived importance of gentrification among neighborhood stressors reinforces the need for longitudinal studies (Diez Roux 2001; Rauh et al. 2001) to explore the role of neighborhood change on stress-related outcomes.

Somewhat to our surprise, youth participants identified similar sets of neighborhood stressors as did adult participants. The adults' discussion of racism and safety concerns, for example, were mirrored in the youth's discussions of experiences of racism and a low sense of safety in their schools. Identifying this unique domain of potential stressor exposures supports growing attention to school-based stress and coping interventions (Pincus and Friedman 2004).

We identified three broad methodological challenges for population-level studies of psychosocial pathways and multiple neighborhood exposures. First, because community-scale administrative indicators are often used in social epidemiology, we attempted to match the stressors identified by community members with publically-available NYC agency data. We were able to locate plausible area-level administrative counterparts for some perceived stressors (e.g., rodent violations, noise complaints, felony violent crimes), but other important stressors had no reliable population-level available data (e.g., police stops, sexual assault, experiences of racism). While it is not realistic (or necessarily advisable) for agencies to fill these gaps, these gaps do create the potential for omitted variable bias in research, particularly in neighborhood effects studies. Additionally, there is a need to directly validate whether these administrative statistics accurately reflect community perceptions. Second, we compared our findings on important community perceived stressors to individual psychosocial stress assessment instruments, such as the Ross-Mirowsky Neighborhood Disorder Scale (Ross and Mirowsky 1999), and found similar gaps. In the context of survey-based assessments, researchers must weigh the trade-offs between missing locally-important response variables, and limiting the interpretability of validated scales by adding items. Third, in our study, participants' perceptions of stressors in their neighborhood were frequently stated *relative* to other areas of the city, across a range of stressors, suggesting that perceived inequality in stressor distribution may be as important, if not more so, than absolute prevalence. There is substantial evidence for health effects of income inequality, independent of absolute income, and likewise it is plausible that both absolute and relative community stressor exposures matter for stress-related health effects.

4.3.1 Limitations

Because our study identified perceived neighborhood stressors in economically disadvantaged communities, with predominantly African American and Latino participants, we do not know how perceptions may differ from those of residents in higher-income communities. Likewise, resources did not allow for male- and female-only groups, and thus we may have omitted some stressors that participants may be reluctant to share in mixed-gender groups. Perceived stigma and sensitivity of the research questions may also have influenced the range of stressors discussed. While we cannot know how participants' prior relationships with each other influenced their comfort in talking about neighborhood stressors, all discussions were lively and lasted the full hour.

4.3.2 Strengths

Participants frequently remarked on the value of having an opportunity to discuss community concerns, and, in fact, requested more focus groups. Given this positive experience, these focus groups may have strengthened the likelihood of future engagement and participant trust in this research process. Dependability of our data are supported by using a structured moderator's guide for consistent data collection, and participant ranking of stressors complemented content analysis to identify prominent stressors and themes. Data collection and analysis were performed by different study team members, with reflexive discussions and iterative data interpretation. Facilitating an open focus group discussion, rather than defining the set of stressors *a priori*, enabled us to explore a broad set of locally-specific perceived stressors.

4.4 CONCLUSION

Engaging community expertise is instrumental for accurate assessment of social stressors for health research. The broad range of neighborhood stressors discussed by community members demonstrates the inter-relatedness of social, political and economic factors that may impact health through chronic stress pathways. Public health community initiatives, policy interventions, and epidemiological studies may benefit from considering community perceptions. Further studies are needed to understand the complex relationships among multiple neighborhood stressors, how they relate to individual stress experience, and how these social and physical stressors may operate through separate and synergistic pathways for health effects.

5.0 DEVELOPING AND VALIDATING A GIS-BASED ONLINE SURVEY INSTRUMENT TO ELICIT SELF-REPORT NEIGHBORHOOD GEOGRAPHY: A PILOT STUDY IN NEW YORK CITY AND PITTSBURGH

Neighborhood context has been linked with numerous adverse health outcomes (Kawachi and Berkman 2003). The 'neighborhood' construct encompasses a range of social processes and environmental factors (e.g., pollution exposures, social cohesion), and there is mounting evidence for the role of neighborhood context independent of individual risk factors (Picket and Pearl 2001; Truong and Ma 2006; Riva et al. 2007). The spatial definition of 'neighborhood' is not static (Diez-Roux 1998), and that the use of administrative areas (e.g., census tracts) as proxies is an important challenge for interpreting neighborhood effects research. As such, there is growing attention to methods for determining the appropriate scale for capturing neighborhood-level exposures, toward refining mechanistic hypotheses and advancing neighborhood effects research (Diez-Roux and Mair 2010).

Neighborhoods are routinely operationalized as administrative small-area units, primarily due to ready availability of data and comparability with other studies, but this presents numerous interpretation challenges. First, the potential for exposure misclassification and spurious associations due to areal unit of aggregation is a longstanding challenge for ecologic analysis [i.e., Modifiable Areal Unit Problem (Openshaw 1984; Maantay 2002)]. Second, activity patterns and perceptions of geography, scale, and boundaries are likely to vary across individuals and communities (Coulton et al. 2013; Coulton et al. 2001; Guest and Lee 1984). Third, appropriate spatial delineations differ by exposure of interest, and are of particular importance for examining effects of multiple exposures. For example, while air pollution levels vary within several hundred feet of a roadway, psychosocial impacts of perceived inequality may operate at a larger scale, and accurately specifying each scale is critical for evaluating separate and combined effects and minimizing uncertainty (Clougherty and Kubzansky 2009). Together, these challenges create the potential for complex confounding, construct misspecification, and systematic exposure misclassification in health research.

Emerging methods to address these challenges – by defining more relevant, hypothesis-driven neighborhood boundaries – fall into two broad categories: "territorial" and "ego-centered" (Chaix et al. 2009). Territorial neighborhoods represent discrete entities, independent of the individuals who inhabit them, and are sometimes defined according to landscape features or political prescription (Merlo et al. 2009). Empirical strategies for defining territorial neighborhood areas use *a priori* criteria to aggregate small area units into larger "neighborhood areas," generally seeking to maximize internal homogeneity in a variable of interest, and to maximize between-neighborhood contrasts [e.g., automated zone design (Cockings and Martin 2005; Openshaw and Rao 1995), optimal zones (Riva et al. 2008; (Martin et al. 2001), FBF statistic (Root et al. 2011), SKATER method (Santos et al. 2010)]. In contrast, qualitative approaches have also been applied to derive territorial areas, including: perceptions of key local stakeholders (Lebel et al. 2007), social theory [e.g., socio-spatial neighborhood estimation (Cutchin et al. 2011)], and subjective assessment of physical environment and population characteristics (Weiss et al. 2007). While these territorial approaches allow for transparent, reproducible neighborhood definition, their utility for health research is hampered by inference limitations associated with the ecological fallacy (Robinson 1950; Greenland and Robins 1994), as they assume that residents uniformly endorse the neighborhood boundary, or share common activity patterns (Kwan 2009).

In contrast, “ego-centric” methods for assessing individual-level neighborhood areas can provide participant-driven measures of lived space, potentially better capturing individual-level neighborhood exposure pathways. Distance-based approaches, such as network buffers around residences, have been used to examine neighborhood walkability and physical activity (Oliver et al. 2007; Lovasi et al. 2009), based on a reasonable average walking distance for errands. However, the assumption that perceived neighborhood space or activity patterns would radiate symmetrically about residential locations may not be realistic or appropriate for other exposures or outcomes of interest.

Drawing from the fields of sociology and geography (Grannis 1998), individual-level mixed-methods assessment approaches have been utilized in neighborhood and health studies. Specifically, neighborhood area and activity pattern maps drawn by study participants have been successfully implemented to understand the role of contextual factors for youth violence (Yonas et al. 2007), risk behaviors (Basta et al. 2010), and community change initiatives (Coulton et al. 2011). For example, in a study examining contextual risk factors for assault victimization, Basta et al. (2010) transcribed study participants’ hand-drawn neighborhood boundaries into a GIS, toward understanding the potential for exposure mis-specification induces by using census tracts as proxies for neighborhoods. Basta et al. found that participants’ self-report neighborhood areas varied substantially in size and shape, overlapped with multiple census tracts and, in some cases, did not contain the participant’s residence. These analyses highlight both the improved accuracy derived from self-report neighborhood information, and the technical challenges of collecting and analyzing hand-drawn map data for large cohorts, specifically time, cost, and potential human error in transcription of hand-drawn boundaries.

Growing familiarity with internet-based interactive mapping platforms (e.g., Google Maps) presents opportunities to integrate GIS-based participatory mapping into assessments of neighborhood-level factors [e.g., VERITAS (Visualization and Evaluation of Route Itineraries, Travel Destinations, and Activity Spaces) (Chaix et al. 2012)], and thus improve sensitivity of individual-level neighborhood metrics. However, the utility of such tools for health research rests on validating the accuracy of mapping instruments across potential 'digital divide' differences in comfort and experience with computers and the internet (Cresci et al. 2010), especially for collecting data from large samples from which in-person administration is not feasible.

Here, we report our process for developing and validating a participatory mapping tool through an online survey of adults in two distinct US cities - New York, NY (NYC) and Pittsburgh, PA (PGH). We aimed to create a flexible tool that could be utilized to address a range of perceived geography questions, and to generate multiple types of data (i.e., polygons, lines, points). For this pilot study, we focus on perceived neighborhood boundaries, and sought to validate the accuracy of mapped neighborhood areas (i.e., polygon shape) against narrative boundary description (i.e., street names). In addition to demographic information, we collected descriptions of individual neighborhood perceptions and behavior patterns, to evaluate systematic differences in neighborhood definition and mapping accuracy. We then compared individual-level mapped neighborhood areas to administrative boundaries in both cities. This is the first attempt, to our knowledge, to validate an online mapping survey tool for public health research.

5.1 METHODS

We developed an online mapping tool to collect perceived neighborhood information from large cohorts, and conducted a pilot study to validate the tool for survey research, using convenience snowball samples in two very different US cities. We performed qualitative and GIS-based quantitative analyses to assess the accuracy of mapped neighborhood areas against narrative boundary descriptions, and to examine spatial relationships between self-report neighborhood areas administrative boundaries. The Institutional Review Board at the University of Pittsburgh approved this study protocol.

5.1.1 Mapping Tool Development

We built a mapping interface to be embedded within online survey questionnaires, to generate geographic data for GIS-based analyses. We used Google Maps (https://maps.google.com) as a base map to take advantage of popular familiarity with its cartographic symbology and interactive tools (e.g., zoom, draw polygon), and because Google Maps' Application Programmer Interface (API) allows for external adaptation. The mapping tool was coded to directly interact with Google Maps API and geographic search engine, such that user-provided information on (a) city of residence and (b) nearest cross-streets to residence were used to pinpoint the latitude and longitude of the user's residential cross-streets (Figure 17, next page). To minimize biases related to differential familiarity with map navigation tools (e.g., zoom), the mapping interface was centered on the user's residential cross-streets, within a pre-set spatial extent of 3 mi^2, as a cartographic scale at which local landmarks and major street names are displayed in Google Maps. Self-report residential cross-streets were chosen, over addresses, to minimize errors related to imprecise address reporting, and to protect participant confidentiality. We adapted the Google Maps API to allow survey participants to draw a polygon around their perceived neighborhood using mouse-clicks to place vertices, double-click to close the polygon, and dragging vertices to modify the shape. Upon finalizing the closed polygon, two geographic files (.kml) were generated: (a) x- and y-coordinates of the residential cross-streets and (b) self-defined neighborhood polygon.

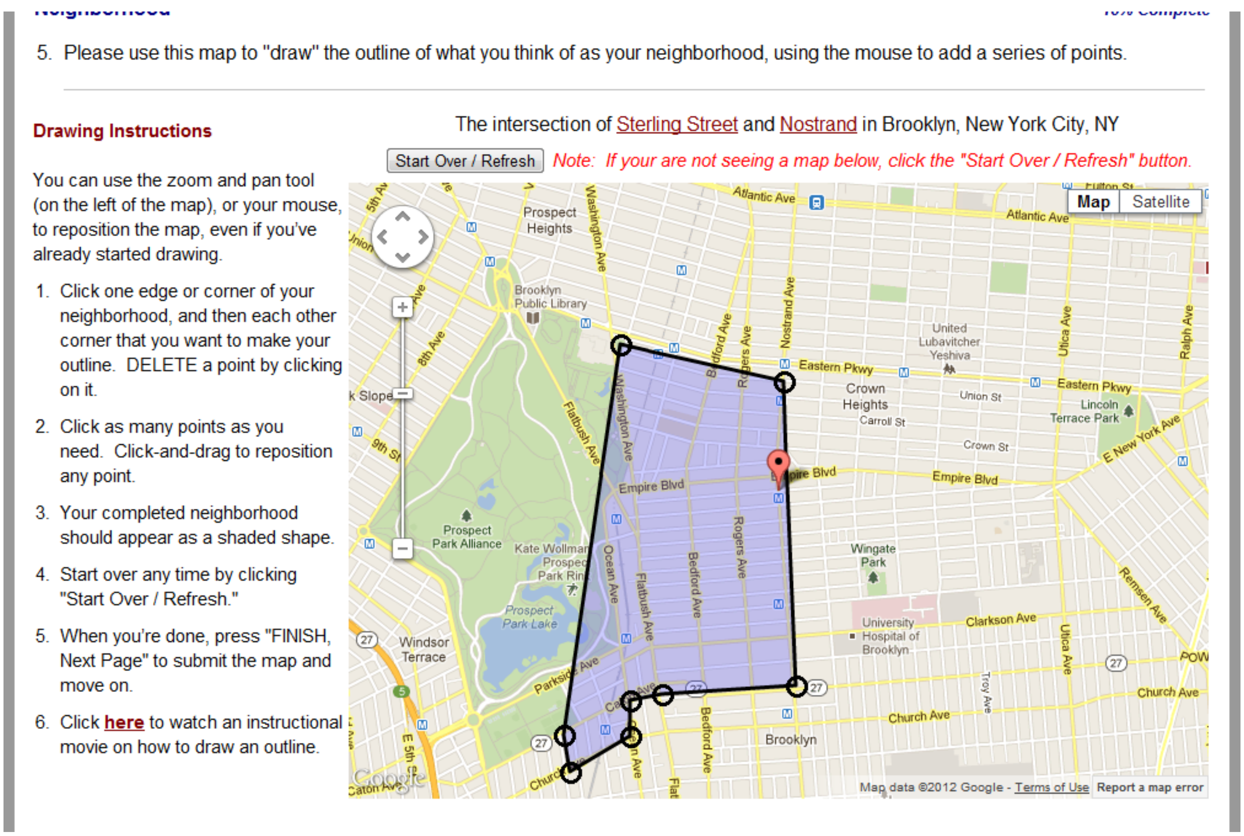


Figure 17. Online mapping tool screen shot

Because we envisioned a survey tool that could be administered without an interviewer present, we emphasized user-friendly and broadly applicable, self-explanatory instructions for the mapping interface. To improve the clarity and accessibility of online mapping instructions, we first pre-tested the mapping interface and collected critical feedback through a convenience sample of friends and colleagues in both cities (n = 21) (data not presented). This online pre-test enabled us to shorten and simplify mapping instructions. To support the step-by-step instructions, we created a Flash video tutorial showing users how to change zoom and orientation, and how to draw a polygon.

Second, we administered a hand-drawn mapping exercise with participants of fourteen focus groups across NYC. We first asked participants to *"draw the outline of what you think of as your neighborhood"* on a printed 8 x 11 inch map centered to the focus group location. As part of the subsequent focus group, participants discussed their personal concepts and definitions of "neighborhood," as well specific boundaries, landmarks, or other factors that influenced how they delineated their neighborhood areas. Based on the diversity of neighborhood definitions described in these focus groups, we decided *not* to explicitly define the term "neighborhood" in the survey mapping item, and to include additional open-response survey items allowing respondents to report individual neighborhood definitions and activities. Focus group study design and sample population are detailed elsewhere (Carr et al. 2012).

5.1.2 Sample recruitment

We aimed to maximize comparability of samples between the two cities by matching non-probability snowball recruitment strategies through two existing networks: (a) university departments of environmental health, including faculty, staff, and graduate students, and (b) local community advocacy and development organizations, broadly affiliated with the National Neighborhood Indicators Project. Invitations were emailed (with 2 reminder emails) to all current network subscribers during March – June 2012, and included a brief description of the study objectives, investigators, and Institutional Review Board approval. Recipients were asked to forward the invitation email to two adult residents of their city. The survey website was closed on August 1, 2012. We used snowball sampling to expand the eligible pool of participants, however, this method did not allow evaluation of overall response rates. Respondents were assigned a random unique identifier, not linked to snowball structure. Participation in the survey was voluntary, anonymous, and no participation incentive was offered.

5.1.3 Data Collection

Participants accessed the online survey platform through a de-identified link. In addition to participants' mapped neighborhood polygons, we collected narrative neighborhood boundaries (i.e., 3 to 5 streets or landmarks outlining their neighborhood) (Q5), open-response questions on activities conducted in their residential neighborhood (Q14-15), and what made then decide where to draw the boundaries (Q6). We queried participant perceptions about the usefulness of the instructions, ease of drawing with the tool, and accuracy of their drawn polygon (Q8-11). We collected socio-demographic information (Q15-20), residential tenure (Q3), and time spent in residential neighborhood during weekdays and weekends (Q12-13). Survey responses were compiled and merged with neighborhood polygons and nearest cross-street points in GIS. The full questionnaire is provided in Appendix E.

5.1.4 Data Analysis

We had four primary analytic objectives: 1) to quantify the geographic relationship between mapped and narrative neighborhood boundaries, as validation of mapping tool accuracy; 2) to examine variation in mapped neighborhood scale and geography; 3) to compare mapped neighborhood areas with administrative unit boundaries, and 4) qualitatively synthesize open-response questions to understand factors that contribute to neighborhood definition and activities. Within each of these objectives, we examined results separately by city and by socio-demographic strata. GIS-based analyses were conducted in ESRI ArcInfo v10 (with Python v2.5), and statistical analyses in SAS v9.2.

To facilitate comparison between mapped and narrative boundaries, we manually transcribed narrative boundaries to geographic polygon files. For consistency with the online mapping tool, we transcribed narrative boundaries in Google Maps. Two analysts (JLCS, ILJ) followed pre-defined transcription protocols, first entering the participant-reported nearest residential cross-streets, neighborhood name, and city into the Google Maps search, recreating the mapping interface centered to the cross-streets. We then used the ‘Draw a shape’ tool to transcribe the narrative boundaries, placing the first vertex at the intersection of the first two bounds (e.g., street name, park border), and drawing a straight line to connect the vertex of subsequent bounds, until the polygon was closed. When not enough, or unidentifiable, boundaries were provided to close the polygon, the mapping item was coded as “unsuccessful.” Successfully transcribed boundaries were assigned the participant ID, and exported as .kml files. For consistency, where parks were reported as a boundary, we used the exterior boundary. Transcription analysts were familiar with local geography and neighborhoods. As a form of non-response analysis, we compared participants who either did not successfully complete the mapping item (i.e., no polygon was generated by the online interface), or did not provide sufficient narrative boundaries for transcription, to those who did.

To validate how accurately respondents were able to represent their perceived neighborhood boundaries using the online mapping tool. We calculated spatial *concordance* between participants' narrative and mapped neighborhood areas, as the proportion of the mapped polygon falling within the corresponding narrative polygon, using the ESRI Intersect tool. Here, concordance represents the probability of the mapping interface capturing the perceived neighborhood area. To evaluate differential accuracy by individual-level demographic factors (age, sex, household income, race, ethnicity, educational attainment, and residential tenure) we compared participants in the 25th versus 75th percentile of concordance using Satterwaite independent t-tests, separately for each city sample. We used the same approach to evaluate differential accuracy by size of mapped neighborhood areas, comparing the proportion of participants with mapped area below or above city-specific median. Open-ended survey items assessing factors influencing where neighborhood boundaries were mapped and activities conducted in- and outside of residential neighborhoods were synthesized using systematic qualitative analysis to generate a list of unique response categories, for each city (Ulin et al. 2001).

To compare mapped neighborhood areas to administrative boundaries, we used participants' self-reported nearest residential cross-streets to assign each participant multiple administrative areas. In NYC, administrative areas included: Police Precincts (PP), School Districts (SD), Community Districts (CD), United Health Fund areas (UHF), and census tracts (CT). In PGH, where PPs and SDs are relatively coarse, comparison administrative units included CT and PGH Department of City Planning neighborhood areas (DCPN). Using the same rationale and process steps as in the validation of mapped areas against narrative descriptions, we quantified the concordance of mapped polygons for each administrative unit, and compared population differences between the 25th and 75th percentiles of concordance.

5.2 RESULTS

5.2.1 Sample population

For the two-city pilot study, we recruited non-probability snowball samples of adult residents of PGH (n = 81) and NYC (n = 93). Sample populations in NYC and PGH were generally comparable (Table 12). Residential tenure – a potentially important predictor of neighborhood perceptions, was longer, on average, among the PGH sample – compared to the NYC sample. Figure 18 (next page) maps the self-report nearest residential cross-streets in each city. Compared to general PGH and NYC populations, study samples over-represented individuals reporting White race, household income more than twice the Federal Poverty Line (FPL), and educational attainment of college degree or more (comparison data not shown).

Table 12. Sample population characteristics

	Pittsburgh (n=81)	New York City (n=93)
Age	Median = 38 (Range 23-69)	Median = 33 (Range 22-71)
Sex	68% Female	52% Female
Race & Ethnicity	83% White	80% White
Residential tenure	Median = 6-10 years	Median = 1-5 years
Household Income	Median = $46-70,000 (2-3x FPL)	Median = $70-93,000 (3-4x FPL)
Educational attainment	Median = College degree	Median = Graduate degree

5.2.2 Neighborhood mapping validation

On average, participants in both cities reported that the mapping instrument was "Very Easy" to use, and self-rated the accuracy of their mapped neighborhood "Very Accurate" in NYC, and "Somewhat accurate" in PGH. Virtually all participants – 99% in NYC and 93% in PGH – provided neighborhood polygons through the survey mapping interface.

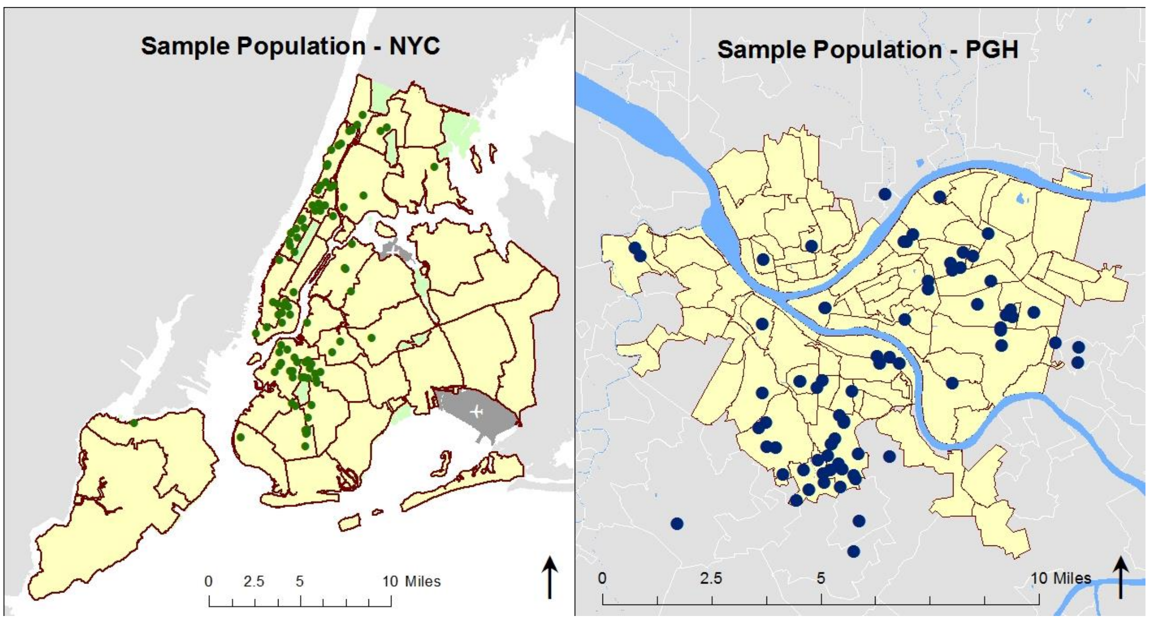


Figure 18. Sample population self-report nearest residential cross-street (with random 500m jitter)

Approximately 75% of participants in each city provided sufficient narrative descriptions of neighborhood boundaries to meet transcription protocol requirements (Table 13, next page). In NYC, participants who did not provide sufficient narrative boundaries were on average younger (data not shown). In PGH, lower household income was associated with narrative completion.

Table 13. Summary statistics - Neighborhood mapping validation

	Pittsburgh (n=81)	New York City (n=93)
Participant assessment of mapping tool*	Most common response (median)	
Self-report ease of use	Very Easy	Very Easy
Self-report accuracy of mapped area	Somewhat Accurate	Very Accurate
Successful completion		
Narrative boundaries	n=59 (73%)	n=71 (76%)
Mapping tool	n=75 (93%)†	n=92 (99%)
Both	n=59 (73%)	n=70 (75%)
Neighborhood Area (km^2)	Mean (SD)	
Narrative boundaries	2.07 (1.77)	0.65 (0.57)
Mapping tool	2.01 (1.6)	1.68 (1.52)
Concordance	74% (22%)	81% (23%)

* 3-level scales (i.e., Very easy, Somewhat easy, Not at all easy)
† n = 1 implausible value removed (area = 0.002 km^2)

Among participants who provided both narrative and mapped neighborhood areas, the size of transcribed narrative versus mapped areas were not statistically different in PGH (mean areas 2.1 to 2.0 km^2, respectively). In NYC, however, mapped areas were, on average, significantly larger than transcribed narrative area [1.7 to 0.7 km^2, respectively (paired t-test $p<0.001$)]. Overall, concordance between narrative boundaries with online mapped areas was 78%, with higher agreement in PGH (mean overlap 81%, versus 73% in NYC). Variance in concordance was similar across cities. We did not observe any statistically significant differences in concordance by individual demographic characteristics, or by size of mapped areas. We found a near-significant difference in mean age between Pittsburgh participants in the 25th versus 75th percentile of concordance, where participants with higher accuracy of mapped areas compared to narrative descriptions (75th percentile) were younger, on average (mean 36 years, SD 9), than participants with lower accuracy (mean 45 years, SD 13).

Participants reported multiple reasons for where they drew their neighborhood boundaries; Table 14 (next page) reports categories of responses, and examples in participants' own words. There was substantial overlap between reason provided by NYC and PGH participants, including knowledge of Administrative boundaries, walking distance, time spent and utilization, familiarity with people and structures, and physical landmarks. Multiple participants in both cities described neighborhood definitions as a function of perceived differences between neighborhoods, and, in NYC, between socio-demographic characteristics of residents. NYC participants also listed transportation (i.e., subway stops) as influencing perceived neighborhood geography.

Table 14. Qualitative factors influencing neighborhood delineation

Factors influencing neighborhood delineation	**Quotations and examples***
Knowledge of Administrative boundaries	Neighborhood association boundaries real estate divisions; street signs (PGH)
Routine walking distance	Area I "*cover on foot*" (PGH); "*daily walking route*" (NYC)
Spend time and use	Leisure walking; dog walking; "*Area I utilize*" (PGH); "*Stores where I stop*" (NYC); "*Work, shop, and play*" (NYC)
Familiarity	Feel comfortable; "*Feel houses in the area are the same*" (PGH); "*I know most people*" (NYC); "*Feel at home*" (NYC); "*Where I could offer welcome and help to someone visiting*" (NYC)
Landmarks	Major streets, parks, natural boundaries, and rivers; "*Railroad tracks*" (PGH); "*Cemetery is a major break*" (PGH)
Community differentiation	"*Point where I would feel I would be in a different neighborhood*" (PGH); "*I tried to stay outside of the adjacent neighborhood*" (PGH); "*Where one ends and the other begins*" (NYC); "*Change in spirit in surrounding areas*" (NYC)
Socioeconomic characteristics (NYC only)	Race, class, and ethnic borders; "*Where the buildings start to get more expensive*"
Transportation (NYC only)	Subway stops

* Unquoted examples represent reasons stated in both cities, unless specifically noted.

Participant reports of activities conducted within and outside of their neighborhood were also similar across city samples. The most common reported activities *within* neighborhoods were shopping and errands. Other commonly-reported activities included: visiting with friends and family, walking for recreation or with a dog, restaurants and bars, and church. Grocery shopping was more often reported as occurring within neighborhood areas in NYC than in PGH, and NYC residents reported travelling outside their neighborhood for specialty item shopping.

Work was more often reported as occurring outside of residential neighborhoods in both cities. Because participants were able to list up to 15 factors, in any order, it was not possible to evaluate differences in accuracy or concordance with administrative units by categories of neighborhood conceptualization. Median self-reported time spent in residential neighborhoods on weekdays was “Some” and “Most” in NYC and PGH, respectively. Participants in both cities reported spending “Most” of weekend time in their residential neighborhood.

5.2.3 Comparison of administrative areas and self-defined neighborhoods

Among NYC participants, the concordance was 77% or higher for UHF, PP, CD, and SD areas, with similar variance across units (SD 21 to 26%), but only 14% for CTs (Table 15, next page). Among PGH participants, self-defined neighborhood areas were more strongly concordant with DCPN areas (76%) than with CTs (45%). We did not find significant differences in socio-demographic characteristics between participants in the 25th versus 75th percentile of concordance, in either city.

Table 15. Summary statistics - Self-defined neighborhoods compared to Administrative areas

New York City (n=92)	**Mean % Concordance (SD)**
Census Tracts (n=2116)	14.3% (16.1)
United Health Fund Areas (n=34)	84.8% (20.6)
Police Precincts (n=78)	77.6% (26.4)
School Districts (n=32)	81.8% (24.0)
Community Districts (n=59)	84.8% (22.7)
Pittsburgh (n=67)	
Census Tracts (n=139)	45.2% (32.9)
DCP Neighborhoods (n=94)	76.4% (33.9)

5.3 DISCUSSION

Developing a flexible tool for describing perceived neighborhood geography can enable specification of neighborhood-level exposure pathways and interventions. Moving beyond analytic challenges of interpreting administrative areas and areal aggregations, to quantitatively characterizing perceived neighborhood area, for individuals and groups, enables more refined understanding of overlapping operational scales within and among neighborhoods. Furthermore, information on population sub-groups that may differ in neighborhood perceptions, and thus systematic misspecification of neighborhood effects, can help identify mechanism for persistent health disparities. Here, we provided a reproducible quantitative and qualitative approach for assessing self-defined neighborhood areas and clarifying neighborhood conceptualization. We used narrative boundaries to validate the accuracy of the mapping tool, and then used perceived neighborhood areas to evaluate spatial concordance with administrative boundaries, in each city.

Systematically assessing the accuracy of self-report mapped neighborhood geography in two distinct cities demonstrated the feasibility of collecting perceived neighborhood information through a mapping interface embedded in an online survey. Geographic concordance between mapped areas and narrative boundaries did not differ by individual-level socio-demographic characteristics in our sample, and was similar in magnitude and variance across cities. We assumed that providing narrative boundaries would be more accessible for participants, compared to mapping perceived boundaries in a Google Maps-based interface, and, thus, that narrative descriptions would better represent "true" perceived neighborhood boundaries, compared to the mapped area. Further, participants reported high levels of ease and perceived accuracy of their mapped neighborhoods. This apparent greater facility with a mapping interface than narrative reporting of boundaries could be a function of familiarity with internet mapping platforms among our samples, relative to orientation on the ground. Alternatively, lower completion rates for narrative descriptions could be an artifact of conservative manual transcription protocols (e.g., requiring closed polygon). Similar online platforms for collecting self-report neighborhood information in digital form, such as VERITAS (Chaix et al. 2012), have relied on in-person survey interviews, where the interviewer input geographic boundaries and the participant confirmed accuracy. Our validation suggests that unassisted online survey mapping items may be a reliable alternative to in-person administration, which could minimize costs, increase sample size, and avert potential response bias from in-person administration.

Evaluating exposure misclassification induced by using administrative area as neighborhood proxies is useful for identifying optimal units of aggregation for population-level investigations. Given previous findings for perceived neighborhoods being smaller than administrative areas (e.g., Yonas et al. 2007) and best GIS-based assessment practice to use the finest unit of population aggregation [especially for assessing disparities (Maantay 2002)], we were surprised to find that perceived neighborhoods in both cities were more quantitatively concordant with relatively coarse administrative units, compared to census tracts. Assessing individual-level exposures to discrete pollution sources, hazards, or assets (e.g., roadways, dry cleaners, alcohol outlets, healthy food vendors), or to continuous processes (e.g., model-based air pollution concentrations, elevation), is amenable to aggregation at multiple geographic scales, including self-report neighborhood areas. However, important data describing the physical and social environment are generally only available in aggregate (e.g., violent crime rates, socioeconomic conditions). As such, population-level neighborhood effects research has largely utilized distance-based metrics (i.e., radial buffers) or census tracts as proxies for neighborhood areas. While these approaches have to some extent facilitated comparisons across studies and locations, the limited interpretability of neighborhood construct, and potential for unmeasured spatial confounding or misspecification, require refined assessment approaches. Our findings suggest that census tracts are not necessarily the best administrative proxy for perceived neighborhood areas, and propose a metrics for identifying which areal units may best match (i.e., minimize Type 1 error) perceived neighborhood geography.

Qualitative information about factors that influence perceived neighborhood geography, and types of activities conducted within and outside of these boundaries, strengthened interpretability of self-defined neighborhood areas and quantitative analyses. Some reported factors influencing perceived suggest activity patterns and physical exposure pathways, such as land use and topographic features (e.g., major roads, landmarks, rivers, cemeteries), distance (e.g., walking distance), and utilization (e.g., area covered running errands). This conceptualization of neighborhood was echoed by participant reports of spending ‘most’ of their weekend time in their residential neighborhoods, and ‘some’ (NYC) or ‘most’ (PGH) of weekday time. Other neighborhood delineation factors were based on more social notions of comfort, belonging, and perceived differences from neighboring areas. This self-definition relative to other places or people resonated with previous focus groups findings of perceptions of neighborhood stressors characterized relative to other areas (Carr et al. 2012). Likewise, the approach of delineating neighborhood areas – empirically (Chaix et al. 2009) or subjectively (e.g., Weiss et al. 2007) - based on socio-demographic homogeneity has been used before; however, these factors were only reported by NYC residents in our sample, indicating that this approach may be appropriate for some places and not others.

The richness of qualitative definitions of neighborhood reveals the range of factors that contribute to “neighborhood,” and future assessments could provide structured survey item (rather than open-response) for respondents to rate what is their primary reason. In future applications, queries targeting specific neighborhood definitions (e.g., physical structures and borders, versus community social dynamics) could aid in developing mechanism-specific investigations.

5.3.1 Strengths

The primary strength of this analysis was the utilization of quantitative and qualitative methods to describe individual-level perceived neighborhood geography. While there is no "gold standard" metric for assessing geographic precision or misclassification, our approach to quantifying concordance, assessing differential concordance by socio-demographic characteristics, and qualitatively assessing self-rated accuracy and neighborhood definition support the viability of online mapping survey instruments for public health research. We piloted the online mapping tool in two cities with distinct urban design, transportation patterns, and residential mobility. We utilized low-cost, broadly-recognizable Google Maps interface to maximize accessibility of the tool for future public health and community applications.

5.3.2 Limitations

The results of neighborhood geography validation, and the definitions and activities associated with residential neighborhoods, are not generalizable, and reflect the sample population (e.g., majority white race, employed, high educational attainment). Analytically, our validation method calling for narrative boundary transcription is time-consuming and computationally intensive. In the context of neighborhood effects research, our focus on residential neighborhood, to the exclusion of other potentially important places (e.g., work, school neighborhoods) is an important limitation for fully characterizing exposure pathways, however, the tool is sufficiently flexible that future applications could query perceptions of multiple lived environments.

5.4 CONCLUSIONS

Our pilot study demonstrated the feasibility of collecting perceived neighborhood geography information through an online survey platform. An online tool for elucidating neighborhood definitions across large populations can help investigators to identify specific mechanisms, clarify their operational scale, and craft multi-level hypotheses for neighborhood effects on health. Better understanding operational scales for these mechanisms may provide critical data for designing health interventions and identifying upstream drivers.

6.0 ECOLOGIC SOCIAL STRESSORS, PERCEPTIONS OF NEIGHBORHOOD STRESSORS, AND PSYCHOLOGICAL DISTRESS ACROSS NEW YORK CITY

Given recent evidence for combined effects of chemical and non-chemical stressors, there is growing interest is validating social stressor exposure measures for environmental epidemiology. The stress process paradigm describes a multi-stage process in which an external *stressor* (an event or condition) overwhelms an individual's perceived coping capacity and resources (Cohen 1995). Within this process, appraisal of stressor exposures mediates individual-level physiologic stress response (Cohen 1998). However, the extent to which administrative indicators commonly used in epidemiological investigations reflect individual-level perceptions of community stressors (or mental health sequlae) is not well understood (Schulz et al. 2008). Survey methods provide one approach for understanding relative construct validity across ecologic stressor indicators, toward minimizing exposure misclassification and unmeasured confounding.

Here, we use survey data to assess relationships between administrative social stressor indicators and individual psychological distress across New York City (NYC) communities, toward developing a validated set of publicly-available indicators for use in an epidemiological investigation of the separate and combined effects of social stress and air pollution on childhood asthma in NYC.

6.1 METHODS

6.1.1 Survey sampling

We aimed to sample 1000 adults contacted through Random Digit Dial (RDD) NYC landline and cellular phone numbers. To be eligible, participants needed to be current NYC residents, over the age of 18, and speak either English or Spanish. In households with multiple eligible adults, the adult with the most recent birthday was eligible. We aimed to sample and additional 500 adults through a voluntary, standing survey panel (contracted through Survey Sampling International), where eligible participants self-administer the survey through an online platform. We aimed for a spatially-representative sample, and set *a priori* sampling density targets corresponding to Borough-level population distributions: roughly 17, 31, 20, 27, and 5% from the Bronx, Brooklyn, Manhattan, Queens, and Staten Island, respectively. The survey was repeated (without RDD replacement) in summer (June – September 2012) and winter (December – March 20012-2013) seasons. Participants were offered a $10 gift card incentive.

6.1.2 Survey instrument and implementation

To develop a locally-appropriate and comprehensive survey instrument, we first conducted 14 focus groups across NYC to collect information on community-reported perceptions of important neighborhood stressors (Carr et al. 2012). Validated survey scales were then identified to assess perceptions of a range of neighborhood stressors, corresponding to community priorities, and to assess multiple aspects of the stress process paradigm, including: personal experiences, perceptions of neighborhood conditions, individual and community-level protective factors (or buffers), individual perceived stress, and mental health (Table 16). The full instrument is provided in Appendix F.

Table 16. Survey scales

Stress process construct	Scale	Citation
Personal experiences & Perceived social standing	Stressful Life Events scale (SLE) from the National Comorbidity Study Everyday Unfair Treatment (EUT) Hurricane Sandy MacArthur Ladder (ML)	Adapted from Kessler et al. 1998 Sternthal et al. 2011 Adapted from Kessler et al. 2008 MacArthur Network on SES & Health
Perceived neighborhood conditions	Neighborhood Physical and Social Disorder (NPSD) Neighborhood Violence (NV) Air quality	Ross and Mirowsky 2001 Sampson and Rauderbush 1997 NA (modeled on NPSD item structure/ response options)
Individual-level buffers & Affect	Interpersonal Support Evaluation List (ISEL) Sense of control (Ctrl) Optimism (Opt)	Cohen et al. 1985; Martire et al. 1999 Lachman and Weaver 1998; Pearlin and Schooler 1978 Scheier et al. 1994
Community-level buffers	Social Capital (SCap) Social Cohesion (SCoh)	Sampson et al. 1997 Araya et al. 2006
Perceived Stress	Cohen Perceived Stress Scale (PSS)	Cohen et al. 1983
Psychological distress	MMPI-2 Anxiety Scale (MMPI Anx) CES-D Depression Scale (CES-D) Spielberger Trait Anger Expression Inventory (TAEI) Self-report (SR) lifetime depression diagnosis (SRD) SR mental health treatment in past year (MHT)	Butcher et al. 1989 Radloff 1977; Irwin et al. 1999 Spielberger et al. 1995 NYC DOMHM CHS 2009 NYC DOMHM CHS 2009
Asthma & Self-rated general health	ISAAC Asthma Phase Three Core Questionnaire (ISAAC) Self-rated general health	Asher et al. 1995 NYC DOMHM CHS 2009

* Modified to capture community-reported stressors (i.e., transportation, police presence, rats and vermin).
† Depending on the number of children in the household.

Building on a community-engaged process to identify important perceived stressors across diverse NYC communities (Carr et al. 2012), we added three survey items to the NPSD scale, covering perceptions of neighborhood transportation, rats and vermin, and police presence (Table 17). In addition, we developed a Likert-type scale to assess perceptions of neighborhood air quality. In addition to demographic and residential neighborhood information, we used the ISAAC scale to collect information on individual and family asthma status. To reduce participant burden (i.e., time) we used validated shortened versions where available (PSS 4-item, CES-D 10-item), and in some cases opted to condense scales (i.e., SCap, SCoh, ISEL).

The RDD telephone surveys were implemented by trained administrators at the Survey Research Program of the University of Pittsburgh Center for Social and Urban Research (UCSUR), and entered into customized computer-assisted telephone interview (CATI) software. Administrators assessed the eligibility of participants, and obtained informed consent before any survey responses were collected. Participants were given the option to complete the survey in English or Spanish. The order of survey scales was fixed to avoid priming for mental health scales and optimize flow by grouping scales with similar response option structures.

Online survey panel respondents were provided with an anonymized link via email, and were able to save and re-start the questionnaire. Online participants were asked to complete a neighborhood mapping item, in which they were instructed to *"Draw the area that you think of as your neighborhood."* The mapping interface was built upon Google Maps and utilized native drawing tools. Standardized geographic parameters and a Flash tutorial video were provided to minimize differential accuracy in self-report neighborhood areas by computer-based mapping familiarity. Development and validation of the online mapping survey tool are detailed elsewhere (Shmool et al. *in preparation*).

The University of Pittsburgh Institutional Review Board approved all human subjects research protocols in this study.

6.1.3 Area-level administrative data

We assembled publicly-available, citywide indicators of area-level stressor prevalence from various NYC agencies, covering multiple chronic stressor constructs, including crime, built environment, air quality, and socioeconomic position (SEP) (Table 2). Administrative indicators of social stressors were reported at four areal units: Police Precincts (PP) (n = 74), Community Districts (CD) (n = 59), United Health Fund areas (UHF) (n = 34), and 2010 census tracts (USCT) (n = 2,126). Tract-level census data were aggregated to UHF areas using proportional areal weights. Data quality and inclusion criteria for administrative social stressors indicators are detailed elsewhere (Shmool et al. 2014). We aimed for administrative reporting periods concurrent or immediately preceding survey implementation, where available. Administrative indicators were selected based on community-reported perceptions of important neighborhood stressors (Carr et al. 2012) stressor constructs in psychosocial stress literature; however, corresponding administrative data were not available in all cases (e.g., counts of Stop-and-Frisk police stops per police precinct).

Air quality data were drawn from the New York City Community Air Survey (NYCCAS) annual pollution concentration surfaces of nitrogen dioxide (NO_2), particulate matter with diameter < 2.5 microns ($PM_{2.5}$), wintertime sulfur dioxide (SO_2), and summertime ground-level ozone (O_3) (Matte et al. 2013; Clougherty et al. 2013), summarized as mean concentration within UHF areal units.

Table 17. Area-level administrative stressor indicators and corresponding survey items assessing perceived neighborhood conditions

	Administrative area-level measures			Survey items and scales		
	% per area population	*Data source, year*	*Areal unit*	*Survey items and summed scales*	*Response form*	*Instrument*
CRIME	Felony Assault Felony Murder Felony Burglary	NYPD, FY 2011, FY 2012 2-year mean	PP (n = 75)	*There is a lot of crime in my neighborhood.* *My neighborhood is safe.*	Likert 1-4, collapsed to binary	NPSD (Ross & Mirowsky 2001)
				The police presence in my neighborhood is more beneficial than stressful.		* Not validated
				During the past 6 months, has anyone used violence against you or any member of your household anywhere in your neighborhood?	Binary Y/N	NV (Sampson et al. 1997)
BUILT ENVIRONMENT	Small parks not acceptably clean	NYC Parks Department, FY 2009	CD (n = 59)	*My neighborhood is clean*. [reverse-coded] *Houses and apartments in my neighborhood are well taken care of.* [reverse-coded] *Rats and vermin are common.** *There are lots of abandoned buildings.* *Vandalism is common.*	Likert 1-4, collapsed to binary	NPSD (Ross & Mirowsky 2001)
	Sidewalks not acceptably clean	Mayor's Office of Operations (MOoO), FY2009	CD			
	Serious housing violations among occupied rental units	Dept. of Housing Preservation and Development, 2009	CD			
	Crowding (>1 occupant per room)	US Census American Communities Survey (ACS), 2005-2009	UHF (n = 34)	Physical Disorder (n=8 items) Social Disorder (n=8 items) (see Appendix F page 156 for complete list of items)	Mean score of Likert 1-4 items	
AIR QUALITY	Average NO_2 (ppb) Average $PM_{2.5}$ (µg/m^3) Average SO_2 (ppb) Average O_3 (ppb)	DOHMH, New York City Community Air Survey (NYCCAS), 2008-2010	UHF (n = 34)	*The air in my neighborhood seems worse than in other neighborhoods.* *I am bothered by pollution from cars, trucks, or buses in my neighborhood.* *I am bothered by air pollution from industry or other pollution sources in my neighborhood.*	Likert 1-4, collapsed to binary	* Not validated
SEP	Household income < 200% Federal Poverty Line (FPL) Unemployment Non-White racial composition Less than High-school education Gini coefficient (income inequality)	ACS 2008-20012	UCST (n = 2126) UHF	*Where do you think you stand at this time in your life relative to the rest of NYC residents?* *Where do you think you stand at this time in your life relative to other people in your neighborhood?*	Continuous (lowest standing =1, highest=7)	ML (MacArthur Network on SES & Health)
				Unfair treatment and experiences of discrimination in day-to-day life (n=5 items) (see Appendix F, page 166 for full list of items)	Continuous (1-6, Never to Almost everyday)	EUT (Sternthal et al. 2011)

6.1.4 Statistical analyses

We used linear multi-level regression to quantify associations between area-level administrative stressor indicators (independent variables) and self-report perceptions of neighborhood conditions and stress experience (dependent variables). A random intercept accounts for nesting of participants in administrative areas. To evaluate the utility of a multi-level modeling framework, we used unconditional variance models (or "empty" models) to partition the variance arising from within and between administrative areas. Empty models were estimate using a random effect for each administrative unit (PP, CD, UHF) and dependent variables representing multiple survey scales, including perceived disorder (NPSD), perceived stress (PSS), psychological distress scales (MMPI Anx, CESD), and perceived buffers (ISEL, Opt, Ctrl, SCap, Scoh). Inter-class Correlation Coefficients for perceived disorder and perceived buffers indicated 16-21% of variance attributable to between-area differences. Variance in perceived stress and psychological distress endpoints was 1-5% attributable to between-area differences. As such, we used a varying intercept regression model with an area-level predictor for all models, for consistency, parameterized as follows,

$$y_{ij} = \beta_{00} + \beta_{01} w_j + b^*_{0j} + \varepsilon_{ij}$$

Where y_{ij} is the observed effect for individual i nested in areal unit j, β_{00} is the average area-level mean (fixed effect), b^*_{0j} is the j-area-specific deviation around the average areal-level mean (random effect), and β_{01} is the expected increase in b_{0j} per IQR change in area-level predictor *w* (fixed effect). All area-level independent variables were standardized to inter-quartile range (IQR) distributions, to facilitate comparisons across diverse indicators.

Specifically, we separately tested four questions about the relationships between area-level stressors and individual-level perceptions and outcomes:

1) Do objective area-level measures of social stressors predict individual-level perceptions of neighborhood conditions (Model A);
2) Do objective area-level measures of social stressors predict individual psychological distress? (Model B); and
3) Are associations between area-level social stressor measures and individual-level psychological distress (Model B) modified by individual- or community-level buffers? We hypothesized that participants reporting higher levels perceived buffers would have weaker association.

All models were adjusted for individual-level characteristics – borough of residence, age (18 - <25, 25 - <35, 35 - <45, 45 - <55, 55 - <65, and ≥ 65 years), sex, neighborhood tenure (< 1 year, 1 -5, 5 – 10, and more than 10 years) – and sampling covariates – season (summer, winter) and recruitment frame. We tested differential associations across individual-level characteristics, including: age (over 45 years old vs. less than), sex, race (non-white vs. white), Hispanic ethnicity, education (BA or more vs. less than BA), household income (below 2x FPL vs. above), and neighborhood tenure (more than 10 years vs. fewer), for all models. Additionally, we tested adjusting models for impact of Hurricane Sandy – an acute stressor which occurred in between winter and summer sample (October 2012) – as a categorical variable defining impact as reported injury or life threatening situation to self or a loved one, no impact (winter), or no impact (summer). We did not adjust final models for Sandy impact to prevent over-adjustment for season, which appeared to be a more potential important confounder.

6.2 RESULTS

6.2.1 Area-level stressor indicators and average pollutant concentrations

We observed wide spatial variation in area-level administrative indicators and NYCCAS area-average concentrations (Table 18, next page). Area-level indicators were reasonably normally distributed.

Table 18. Summary statistics for area-level stressors and average air pollutant concentrations

Area-level Indicator	Mean (SD)	IQR
Felony Assaults per 10,000	2.2 (1.6)	2.2
Felony Murders per 10,000	0.06 (0.04)	0.05
Felony Burglary per 10,000	2.4 (2.2)	1.0
% Small parks not acceptably clean	21.7 (21.1)	16.1
% Sidewalks not acceptably clean	2.8 (2.1)	2.4
Serious housing violations per 1,000 occupied rental units	43.3 (43.0)	47.7
% Crowding in occupied residential units	7.6 (6.5)	4.9
% Households with annual income < 200% FPL (UHF)	36.9 (14.0)	20.3
% Unemployment among population > 25 years old (UHF)	9.6 (2.9)	0.06
% Non-White racial composition (UHF)	52.7 (24.3)	3.9
% Less than high school education among population > 25 years old (UHF)	19.8 (9.3)	9.2
Gini coefficient (income inequality) (UHF)	0.45	47.6
Average NO_2 (ppb)	25.5 (5.5)	6.0
Average $PM_{2.5}$ ($\mu g/m^3$)	11.2 (1.4)	1.7
Average SO_2 (ppb)	5.5 (2.0)	3.2
Average O_3 (ppb)	24.6 (2.3)	3.2

6.2.2 Sample population

Response rate for RDD landline and cellular sampling frames were low (5.5%), reflecting low contact rates (38.8% summer; 39.9% winter) and cooperation rates (14.8% summer; 13.1% winter) (Table 19, next page). Response rates were similar across RDD frames and seasons. Across seasons, sample participants were drawn approximately 34% from RDD landline, 10% from RDD cellular, and 55% online frames. NYC borough of residence for our sample was approximately proportional to census proportions, except a higher proportion of cellular sample from the Bronx, and lower proportion from Manhattan. Survey participants were drawn from 95, 97, and 100% of PP, CD, UHF administrative units, respectively, with counts per unit ranging from 4-57, 7-57, and 10-97, respectively. Samples were approximately equal in each season (774 summer, 775 winter).

Table 19 (next page) details distributions of participants by individual-level covariates, season, and sampling frame. Participant characteristics were similar across seasons and sampling frames, with some exceptions: higher proportion of landline respondents reported white race, age over 65, and neighborhood tenure over 10 years. Compared to NYC census statistics (ACS 2008-2012), our sample under-represented individuals aged 45 - 65, with less than High School education, and males, and over-represented low-income households (annual income < FPL) (Table 19). Among winter frame participants, 2.2% (n = 17) of participants reported acute experiences during Hurricane Sandy.

Table 19. Summary statistics - sample population

	Summer (June-Sept 2012)			Winter (Dec-March 2013)			Overall	NYC†
Contact method	Landline RDD	Cell RDD	Online panel	Landline RDD	Cell RDD	Online panel		
n (% or season)	256 (33.1)	90 (11.6)	428 (55.3)	277 (35.7)	72 (9.3)	426 (55.0)	1549	--
Response rate %	6.1	5.0	NA	5.6	4.5	NA	5.5%	--
Socio-demographic characteristics*								
	n (%)			n (%)			n (%)	%
Borough								
Bronx	36 (14.7)	21 (24.1)	74 (17.8)	45 (16.4)	17 (23.6)	68 (16.1)	261 (17.2)	16.9
Brooklyn	73 (29.8)	25 (28.7)	106 (25.5)	81 (29.6)	25 (34.7)	136 (32.2)	446 (29.4)	30.6
Manhattan	48 (19.6)	8 (9.2)	104 (25.1)	57 (20.8)	7 (9.7)	88 (20.9)	312 (20.6)	19.5
Queens	70 (28.6)	27 (31.0)	103 (24.8)	75 (27.4)	19 (26.4)	103 (24.4)	397 (26.2)	27.3
Staten Island	18 (7.4)	6 (6.9)	28 (6.8)	16 (5.8)	4 (5.6)	27 (6.4)	99 (6.5)	5.7
Age								
18 - < 25 years	17 (6.9)	22 (25.0)	55 (13.3)	12 (4.4)	12 (16.7)	81 (19.4)	199 (13.2)	7.8††
25 - < 35 years	20 (8.1)	22 (25.0)	116 (28.0)	23 (8.4)	21 (29.2)	120 (28.8)	322 (21.3)	17.1
35 - < 45 years	35 (14.2)	9 (10.2)	60 (14.5)	48 (17.6)	14 (19.4)	62 (14.9)	228 (15.1)	14.2
45 - < 55 years	51 (20.7)	18 (20.5)	65 (15.7)	50 (18.3)	11 (15.3)	76 (2)	271 (18.0)	13.5
55 - < 65 years	53 (21.5)	12 (13.6)	87 (21.0)	61 (22.3)	9 (12.5)	52 (12.5)	274 (18.2)	10.9
65 years or older	70 (28.5)	5 (5.7)	31 (7.5)	79 (28.9)	5 (6.9)	26 (6.2)	216 (14.3)	12.2
Sex								
Male	86 (33.6)	41 (45.6)	143 (33.7)	98 (35.4)	41 (56.9)	143 (33.8)	560 (36.3)	47.5
Female	170 (66.4)	49 (54.4)	281 (66.3)	179 (64.6)	31 (43.1)	280 (66.2)	982 (53.7)	52.5
Race†††								
White / Caucasian	136 (53.1)	30 (33.3)	257 (60.1)	158 (57.0)	25 (34.7)	226 (53.1)	832 (53.7)	46.4
Black / African American	77 (30.1)	34 (37.8)	95 (22.2)	75 (27.1)	28 (38.9)	111 (26.1)	420 (27.1)	26.6
Asian	10 (3.9)	6 (6.7)	44 (10.3)	17 (6.1)	7 (9.7)	59 (13.9)	143 (9.2)	13.9
Native American	8 (3.1)	1 (1.1)	10 (2.3)	3 (1.1)	2 (2.3)	8 (1.9)	32 (2.1)	0.9
Other	36 (14.1)	24 (26.7)	35 (8.2)	37 (13.6)	15 (20.1)	31 (7.3)	178 (11.5)	15.4
Hispanic ethnicity	39 (15.4)	29 (32.3)	93 (22.1)	42(15.2)	18 (25.7)	97 (23.0)	318 (20.8)	28.6
Employment status††††								
Full-time / self-employed	86 (33.6)	43 (47.8)	195 (45.6)	109 (39.4)	36 (50.0)	179 (42.0)	648 (41.8)	57.0
Part-time employed	24 (9.4)	12 (13.3)	46 (10.8)	20 (7.2)	8 (11.1)	57 (13.4)	167 (10.8)	-
Homemaker	19 (7.4)	3 (3.3)	26 (6.1)	10 (3.6)	2 (2.8)	21 (4.9)	81 (5.2)	-
Student	10 (3.9)	12 (13.3)	36 (8.4)	9 (3.3)	7 (9.7)	53 (12.4)	127 (8.2)	-
Unemployed looking for work	19 (7.4)	11 (12.2)	47 (11.0)	24 (8.7)	10 (13.9)	62 (14.6)	173 (11.2)	6.4
Not looking for work / Retired	95 (37.1)	9 (10.0)	78 (18.2)	102 (36.8)	9 (12.5)	54 (43.0)	347 (22.4)	36.5
Educational attainment								
Less than High School	16 (6.3)	9 (10.1)	13 (3.0)	19 (6.9)	6 (8.3)	21 (5.0)	84 (5.5)	17.8
High School graduate	55 (21.7)	22 (24.7)	65 (15.2)	40 (14.5)	21 (28.2)	65 (15.4)	268 (17.4)	23.4
Some college / vocational	64 (25.2)	27 (30.3)	142 (33.3)	67 (24.3)	28 (38.9)	155 (36.6)	483 (31.3)	22.2
Bachelor's degree or more	119 (46.9)	31 (34.8)	207 (48.5)	150 (54.4)	17 (23.6)	182 (43.0)	706 (45.8)	36.6
Annual household income								
Less than $23,000 (< FPL)	62 (27.1)	25 (29.4)	95 (22.3)	61 (24.0)	23 (32.4)	115 (27.2)	381 (25.6)	10.5
$23,000 - < 46,000 (< 2x FPL)	48 (21.0)	22 (25.9)	103 (24.1)	56 (22.1)	20 (28.17)	103 (24.4)	352 (23.6)	21.3
$46,000 - < 70,000 (< 3x FPL)	46 (20.1)	14 (16.5)	76 (17.8)	38 (14.5)	11 (15.5)	88 (20.8)	273 (18.3)	16.0
$70,000 - < 93,000 (< 4x FPL)	20 (8.7)	12 (14.1)	67 (15.7)	36 (14.2)	11 (15.5)	46 (10.9)	192 (12.9)	10.8
$93,000 – 135,000 (< 6x FPL)	25 (10.9)	8 (9.4)	48 (11.2)	30 (11.8)	2 (2.8)	33 (7.8)	146 (9.8)	12.4
More than $135,000 (> 6x FPL)	28 (12.2)	4 (4.7)	38 (8.9)	33 (13.0)	4 (5.6)	38 (9.0)	145 (9.7)	12.3
Neighborhood tenure†††††								
Less than 1 year	6 (2.3)	8 (8.9)	32 (7.5)	5 (1.8)	8 (11.11)	36 (8.5)	95 (6.1)	-
1 - 5 years	24 (9.4)	26 (28.9)	94 (22.0)	39 (14.1)	20 (27.8)	101 (23.7)	304 (19.6)	9.4
5 - 10 years	35 (13.4)	12 (13.3)	78 (18.3)	27 (9.8)	11 (15.3)	66 (15.5)	229 (15.8)	49.2
More than 10 years	191 (74.6)	44 (48.9)	223 (52.2)	206 (74.4)	33 (45.8)	223 (52.4)	920 (59.4)	38.4
Hurricane Sandy (Oct 2013)								
Injury or life-threatening situation (self or loved one)	--	--	--	6 (2.2)	3 (4.2)	8 (1.9)	--	--
No impact				270 (98.8)	69 (95.8)	418 (98.1)		

* Percentage of the total number of participants who responded to each item. † Population statistics from ACS 2008-2012 5-year estimates. †† ACS age census category: 20-24 years. ††† Percentages ≠ 100 because participants could answer more than one race. †††† ACS labor categories, among population ≥ 16 years: Employed; unemployed; not in labor force. ††††† ACS Tenure categories: Moved in since 2010; moved in 2000-2009; moved in 1999 or before.

6.2.3 Survey summary statistics

Table 20 (next page) summarizes participant reported perceptions of neighborhood conditions, social standing, and experiences of unfair treatment. On average, participants reported low levels of perceived crime-related and physical neighborhood disorder (median Likert score of 2 indicates ‘disagree’ to statements describing disorder). Multi-item scales (e.g. social disorder mean of n=8 items) were not scored for participants with skipped or refused items. Participants reported subjective social standing (i.e., MacArthur Ladder) in the middle of the entire NYC population (median = 4, on 1-7 scale), and slightly higher standing relative to other in their neighborhood (median = 5). The summed reported frequency for six unfair treatment items was left-skewed (median score = 9, for possible range 5-30). Among participants who reported any experiences of unfair treatment, 23% (n = 364) attributed the experience to their race.

Table 21 (page 115) summarizes participant-reported perceptions of buffers and coping resources – potential modifiers of the association between stressors and adverse mental health. Reported individual social support and resources, including optimism and sense of control, were normally distributed. Reported perceptions of community social capital and social cohesion were relatively right-skewed, indicating higher levels of perceived community-level social buffers.

Table 22 (page 115) summarizes participant-reported mental health and perceived stress. The PSS, CES-D, and MMPI Anxiety scales were slightly left skewed, indicating low levels of adverse mental health symptoms, on average. 18% of participants reported lifetime depression diagnosis, and 22% reported mental health treatment in the past year (i.e., counseling or prescription medication).

Table 20. Perceptions of neighborhood conditions and personal experiences

Survey items	Response Categories*	n	Median (SD)	Possible Range
There is a lot of crime in my neighborhood.	1-4 'Strongly Disagree' to 'Strongly Agree' (i.e., Likert levels)	1424	2 (0.8)	1-4
My neighborhood is safe. [reverse coded]	"	1481	2 (0.7)	1-4
The police presence in my neighborhood is more beneficial than stressful.	"	1396	2 (0.8)	1-4
During the past 6 months, has anyone used violence against you or any member of your household anywhere in your neighborhood?	Y/N	1514	Y=243	-
My neighborhood is clean. [reverse-coded]	1-4 Likert levels	1522	2 (0.8)	1-4
Houses and apartments in my neighborhood are well taken care of. [reverse-coded]	"	1460	2 (0.7)	1-4
Rats and vermin are common.	"	1445	2 (0.9)	1-4
There are lots of abandoned buildings.	"	1491	2 (0.7)	1-4
Vandalism is common.	"	1449	2 (0.8)	1-4
Physical Disorder	Mean of 8 items with 1-4 Likert levels	1241	2 (0.5)	1-4
Social Disorder	"	1008	2 (0.6)	1-4
The air in my neighborhood seems worse than in other neighborhoods.	1-4 Likert items	1251	2 (0.8)	1-4
I am bothered by pollution from cars, trucks, or buses in my neighborhood.	"	1339	2 (0.8)	1-4
I am bothered by air pollution from industry or other pollution sources in my neighborhood.	"	1330	2 (0.8)	1-4
Where do you think you stand at this time in your life relative to the rest of NYC residents?	1-7, with highest social standing ranked 7 and lowest standing ranked 1	1479	4 (1.4)	1-7
Where do you think you stand at this time in your life relative to other people in your neighborhood?	"	1501	5 (1.5)	1-7
Unfair treatment and experiences of discrimination in day-to-day life	Sum of 5 items with frequency categories 1-6 from 'Never' to 'Almost Everyday'	1497	9 (4.7)	5-30

* Higher levels indicate more negative perception or experiences.

Table 21. Individual- and community-level perceived buffers

Survey items	Response Categories*	n	Median (SD)	Possible Range
Social capital and social cohesion	Sum of 7 items with 1-4 Likert levels	1033	20 (4.3)	7-28
Social capital	Sum of 3 items with 1-4 Likert levels	1143	8 (1.8)	3-12
Individual social support and resources	Sum of 14 items with 1-4 Likert levels	1214	28 (6.5)	14-56
Interpersonal support	Sum of 6 items with 1-4 Likert levels	1369	12 (3.2)	6-24
Sense of control	Sum of 4 items with 1-4 Likert levels	1394	8 (2.0)	4-16
Optimism	Sum of 4 items with 1-4 Likert levels	1365	8 (2.4)	4-16

* Higher levels indicate higher perceived buffers.

Table 22. Mental health and perceived stress

Survey items	Response Categories	n	Median (SD)	Possible Range
PSS	Sum of 4 items with frequency categories 1-5 ‘Never’ to ‘Very Often’	755	8 (3.3)	4-20
CES-D	Sum of 10 items with frequency categories 1-5 ‘Never’ to ‘Most or all of the time’	914*	23 (7.1)	10-50
MMPI Anx	Sum of 23 items with frequency categories 1-4 ‘Rarely’ to ‘Most of the time’	1366	44 (12.7)	23-92
SR Lifetime depression diagnosis	Y/N	1525	Y = 273	-
SR Mental health treatment in past year	Y/N	1525	Y = 342	-

* Only scored CES-D for participants who answered ≥ 8 items

6.2.4 Model A: Administrative indictors as predictors of individual-level stressor perceptions

Violent crime rates (i.e., assault, murder), but not property crime rates (i.e., burglary) were positively associated with perceived neighborhood crime and safety, but not with perceptions of police presence as ‘more stressful than beneficial’ or with reported direct experiences of violence (Figure 19, page 117). Overall, an IQR increase in area-level assault or murder rates conferred a 2-fold increase in odds of agreeing or strongly agreeing with survey items describing crime-related social disorder. Stratified analyses by individual-level characteristics and season indicate variation in the strength of association, but differences were not statistically significant, except for significantly stronger association between murder rates and perceived crime and safety among white participants, compared to non-white, and stronger association between burglary rates and perceived crime among Hispanic participants, compared to non-Hispanic.

Objective area-level measures of disorder in the built environment (except cleanliness of local parks) were positively associated with perceived physical disorder survey items: upkeep of housing, cleanliness, vandalism, abandoned building, or prevalence of rates and vermin (Figure 20, page 119). Overall, an IQR increase in % unclean sidewalks, housing violation rate among rental units, and % residential crowding conferred approximately 35 to 75% increase in odds of agreeing or strongly agreeing with survey items describing physical disorder (results not shown for latter three items). Similar to analyses of area-level crime rates and perceptions of safety, stratified analyses do not indicate statistically significant differences, except for significantly stronger association between housing violation rates and white participants perceptions of how well-taken care of neighborhood houses and apartments are, compared to non-white participants.

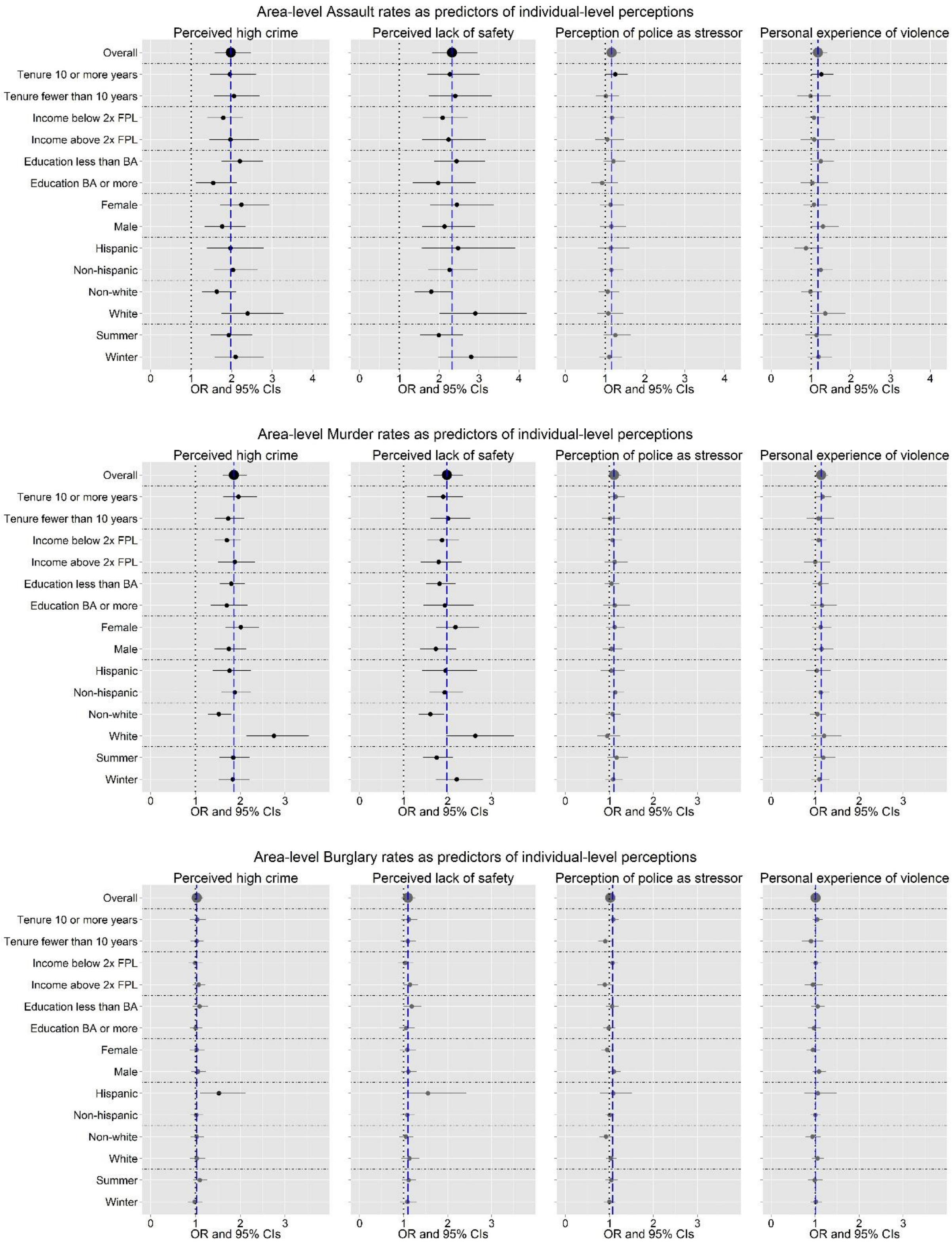


Figure 19. Odds of reporting perceived crime-related disorder per IQR increase in Felony crime rates, overall and by population strata

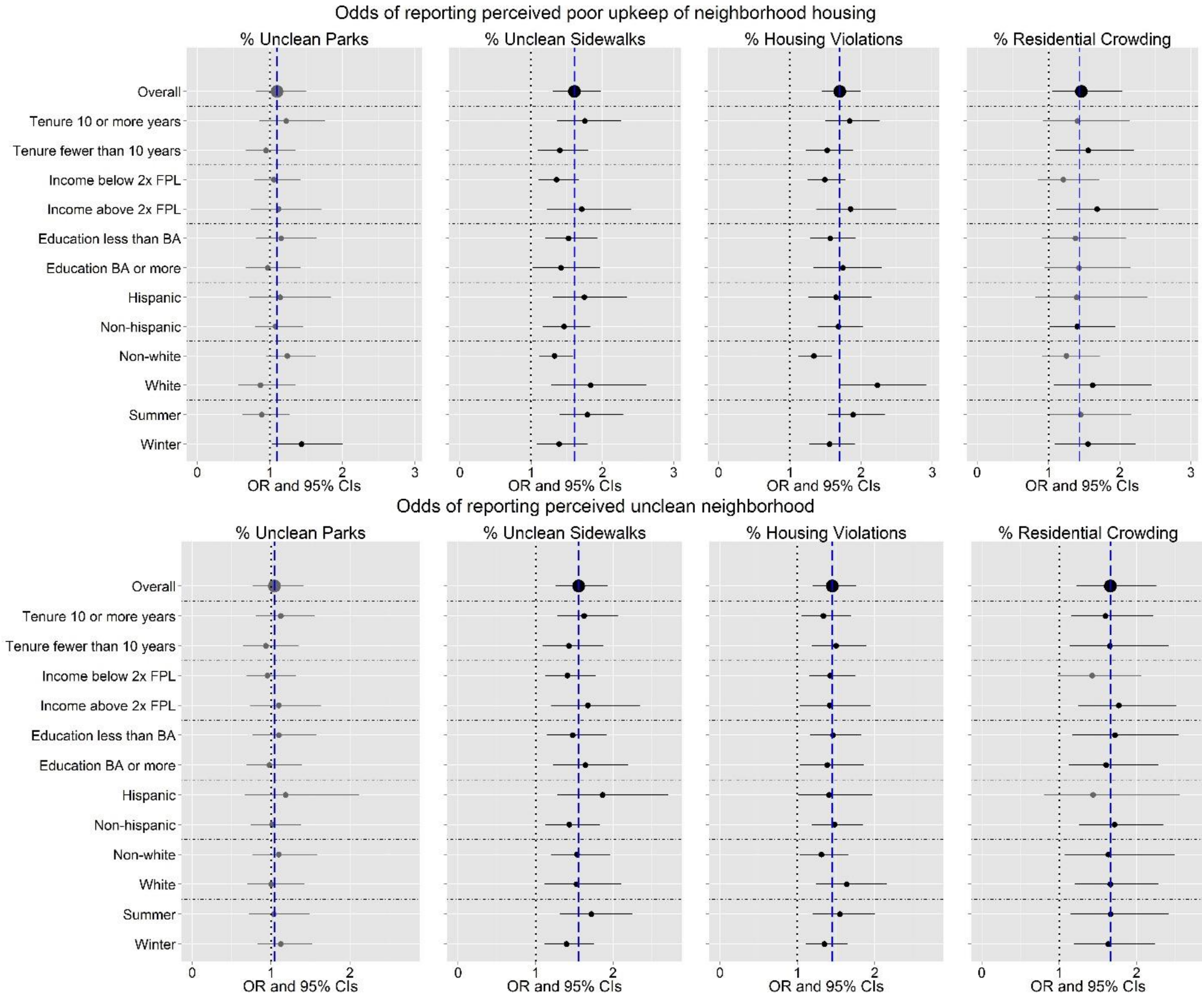


Figure 20. Odds of reporting perceived physical disorder per IQR increase in built environment administrative indicators, overall and by population strata

Area-level SEP measures were not significantly associated with participants' MacArthur Ladder measures of perceived social standing relative to the rest of NYC residents (Figure 21, next page). When considering social standing relative to their neighbors, however, low area-level SEP indicators (but not inequality) were positively associated with higher perceived social standing. In other words, participants living in lower-SEP areas reported higher subjective social standing relative to their neighbors, but not necessarily to the rest of New Yorkers. Frequency of unfair treatment experiences was marginally positively associated with area-level income inequality, but not with other SEP measures.

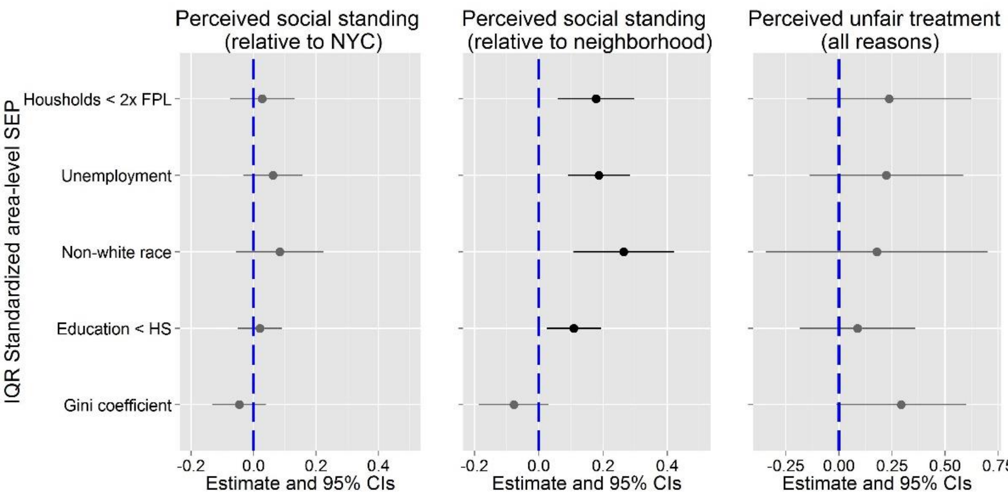


Figure 21. Area-level SEP indicators as predictors of perceived social standing and unfair treatment

Area-average NYCCAS NO_2, $PM_{2.5}$, and SO_2 pollution concentrations, but not O_3, were significantly associated with increased odds of reporting negative perceptions of neighborhood air quality relative to other NYC areas, and in relation to car, truck, and bus traffic, but not to industry or other pollution sources (Figure 22).

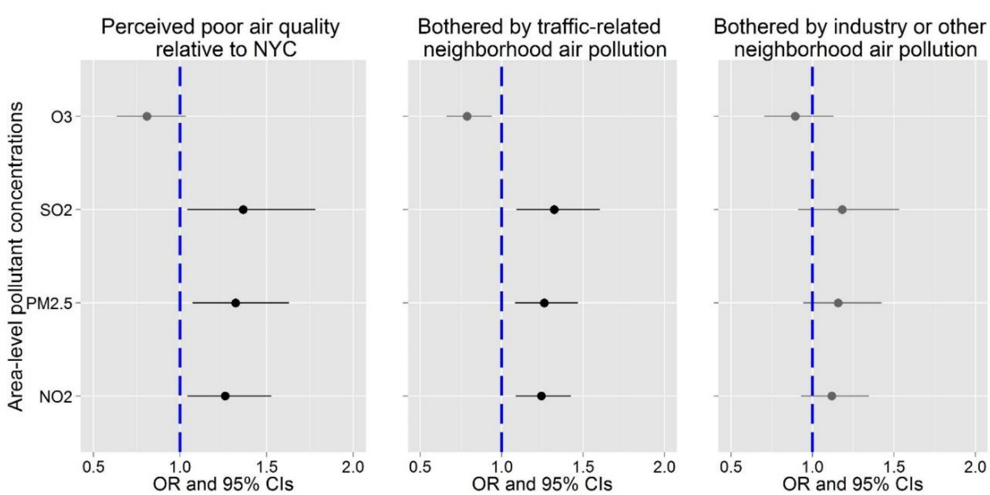


Figure 22. Odds of reporting negative perceived air quality per IQR increase in area-average pollutant concentrations

Across stressor constructs, administrative indicators were similarly associated with perceived physical and social disorder. As such, we evaluate perceived neighborhood disorder as a single measure, in keeping with scale originator's intent (Ross and Mirowsky 2001). Perceived disorder (mean item score for 16-item scale, possible range 1-4) was more strongly associated with built environment administrative indicators (except % small parks unacceptably clean) among long-term neighborhood residents (tenure ≥ 10 years), females, and participants over 45 years old, but did not differ statistically from the rest of the sample.

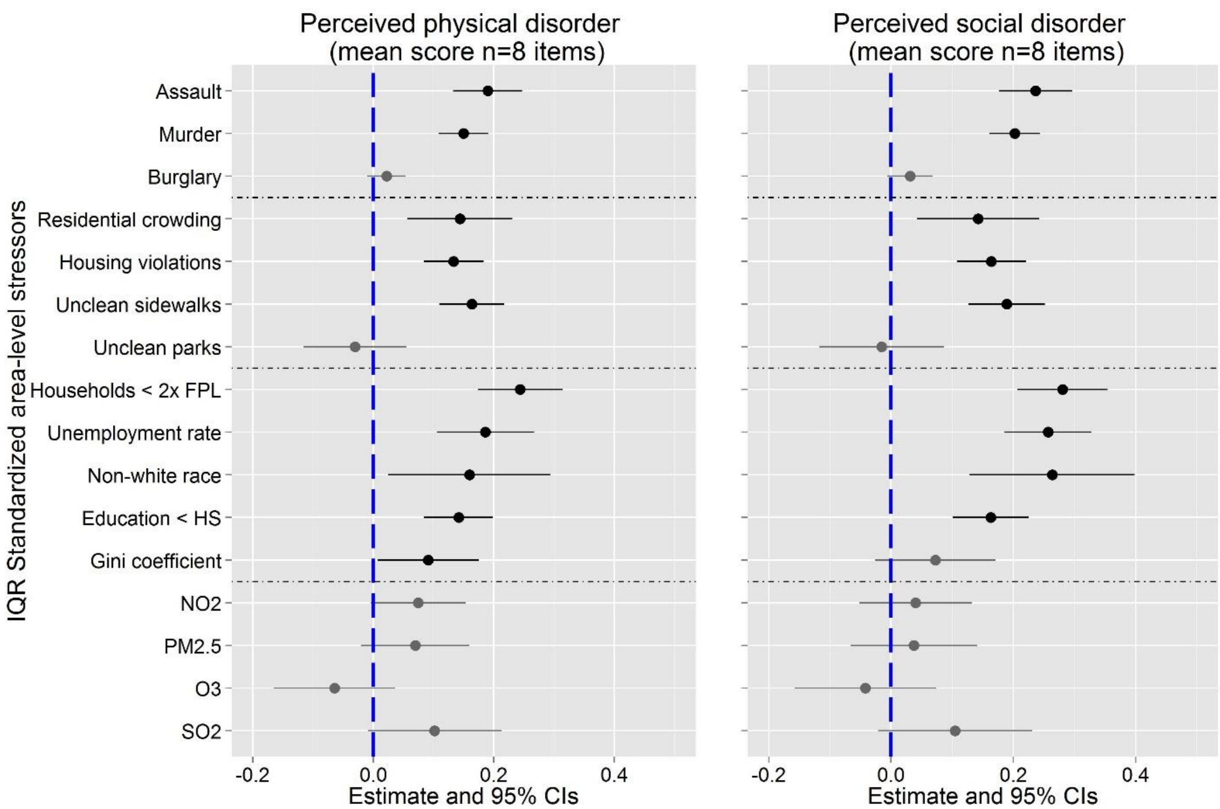


Figure 23. Change in perceived disorder mean score per area-level stressor indicator IQR

6.2.5 Model B: Area-level indicators as predictors of individual-level psychological distress

We carried forward the nine administrative indicators associated with perceived neighborhood disorder in Model A: assault, murder, crowding, housing violations, unclean sidewalks, poverty, unemployment, non-white racial composition, and education (Figure 23, previous page). We then tested these "validated" ecologic indicators as predictors of psychological distress, using four distress scales (PSS, MMPI Anx, CESD, MHT).

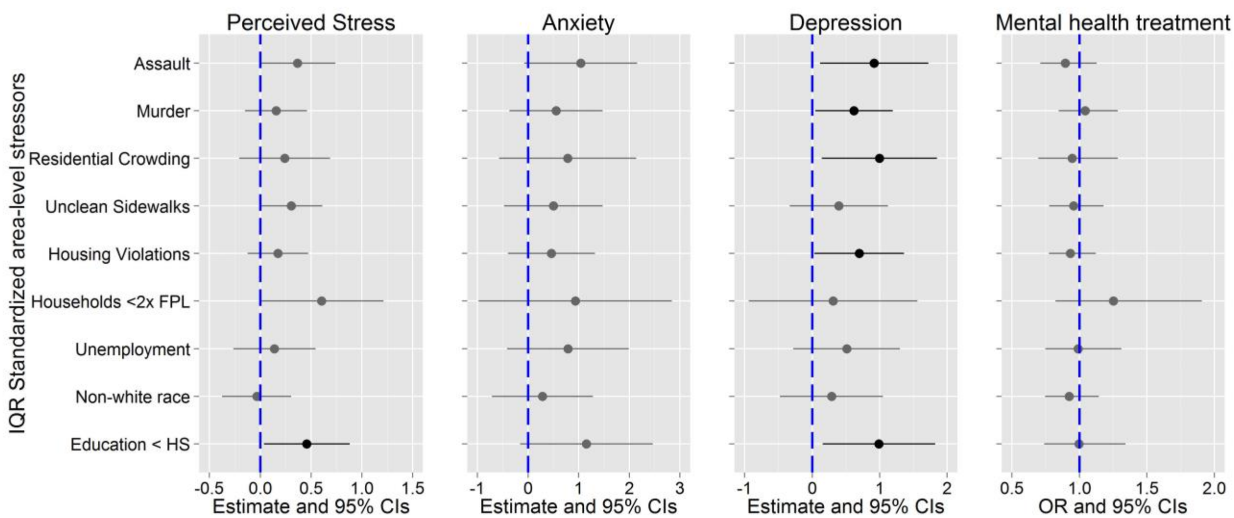


Figure 24. Area-level predictors of psychological distress

Overall, we observed weak positive associations (Figure 24). As with Model A, we observed some variation by individual-level socio-demographic categories, but not systematic biases or statistically significant differences, across scales. Given weak associations, we tested modification of Model B by perceived buffers (ISEL, Opt, Ctrl, SCap, Scoh) by comparing participants in the 25th and 75th percentiles of each survey scale. Across indicators, we observed stronger associations among participants in the 75th percentile of perceived community social cohesion/ capital, and individual sense of control (results not shown), and no meaningful differences by individual interpersonal support or optimism. We did not observe significant interaction for any model.

6.2.6 Limitations

A key limitation of the study was insufficient power and internal variation in dependent variables to detect differences in relatively rare psychological distress outcomes, measured conservatively with composite and diagnostic scales. Lack of information about the recruitment method for the online sampling panel is a key limitation, despite reasonable demographic comparability with participants recruited through RDD frames. Though we designed the survey to assess multiple foci of the stress process paradigm, our sample data was not sufficiently powered to evaluate complex interactions, such as 3-way cross-level interactions by individual socio-demographic characteristics and perceived buffers.

6.2.7 Strengths

This study utilized a spatial recruitment design toward capturing participants from diverse neighborhoods across NYC, and was reasonably representative of the general NYC population. Survey development and scale selection was informed by a community-engaged focus group study to identify important perceived stressors, and we supplemented validated survey scales with items reflecting community-reported priorities (e.g., perceptions of police presence). Our quantitative framework for estimating associations between administrative social stressor indicators, individual perceptions of neighborhood conditions, and psychological distress accounted for clustering of participants within tracts and were adjusted for confounders (i.e., sex, age, residential tenure, season).

6.3 CONCLUSION

Survey methods are one approach for leveraging the stress process paradigm (i.e., stressor appraisal) to assess relative construct validity across ecologic stressor indicators, toward minimizing exposure misclassification and unmeasured confounding. While relationships between social stressors and individual psychological distress appear largely a function of individual-level factors across NYC communities, systematically assessing ecologic stressor exposure indicators is useful for identifying publicly-available indicators suitable for use in population-level epidemiological investigations of the separate and combined effects of chemical and non-chemical stressors. Further research is needed to characterize individual- and community-level stress buffers, and to identify robust ecologic indicators for epidemiological applications.

7.0 CONCLUSIONS

This dissertation proposes advanced geospatial techniques, mixed qualitative and quantitative methods, and community-engaged approaches for robust exposure assessment of non-chemical stressors for social-environmental epidemiology. Using GIS-based ecologic data and spatially informed statistical models, we demonstrated that SEP is an inadequate – and potentially misleading – proxy for social stressor exposures and downstream psychological distress. Further, specifying common patterning across a broad range of stressor constructs minimized spatial confounding among social stressors – and with intra-urban air pollution gradients – and suggested complex susceptibility pathways. We demonstrated flexible approaches for addressing challenges of incongruent units of aggregation in administrative data, assessing (and accounting for) spatial autocorrelation. By engaging individual perceptions of neighborhood scale and meaning, we showed the feasibility of reducing error and bias in exposure assessment through community-driven processes. Likewise, community perceptions and priorities were invaluable for stressor hazard identification, and elucidated the complex relationships among social and physical pathways to psychological distress. Finally, by leveraging a spatial approach and community knowledge for assessing multiple foci of the stress process paradigm, we offer a robust approach to identifying ecologic stressor indicators for social-environmental epidemiology.

APPENDIX A: MODIFICATION OF THE NO_2-BIRTH WEIGHT ASSOCIATION BY MATERNAL SEP CHARACTERISTICS

Table 23. Linear coefficient estimates for NO_2-Maternal SEP interaction model

Covariates	***NO_2 * Maternal Education*** Effect estimate (g)	95% CIs	***NO_2 * Medicaid Status*** Effect estimate (g)	95% CIs	***NO_2 * Maternal Ethnicity*** Effect estimate (g)	95% CIs
Intercept	2818.2	2767.9, 2868.4	2811.2	2780.3, 2842.1	2817.0	2784.2, 2849.8
NO_2 exposure (per 10 ppb)	-16.4	-31.9, -0.8	-14.0	-19.3, -8.7	-15.8	-22.4, -9.2
NO_2 * Maternal Education						
< 9 yrs. [REF]	[REF]	[REF]	--	--	--	--
9 - 11 yrs.	11.4	-6.3, 29.1	--	--	--	--
12 yrs. (High school)	9.6	-7.3, 26.6	--	--	--	--
13 - 15 yrs.	-1.2	-17.9, 15.5	--	--	--	--
16 yrs. (BA)	6.3	-10.3, 22.8	--	--	--	--
> 16 yrs.	3.6	-13.2, 20.4	--	--	--	--
NO_2 * Medicaid status						
No [REF]	--	--	[REF]	[REF]	--	--
Yes	--	--	7.4	-0.02, 14.9	--	--
NO_2 * Ethnicity						
US-born White [REF]	--	--	--	--	[REF]	[REF]
Foreign-born White	--	--	--	--	10.8	0.4, 21.2
US-born Black	--	--	--	--	0.4	-12.9, 13.7
Foreign-born Black	--	--	--	--	-0.7	-15.6, 14.3
US-born Hispanic	--	--	--	--	1.0	-11.4, 13.4
Foreign-born Hispanic	--	--	--	--	4.2	-6.9, 15.3
US-born Asian	--	--	--	--	3.9	-17.9, 25.7
Foreign-born Asian	--	--	--	--	15.5	4.8, 26.1

Table 24. Coefficient estimates for NO_2-Maternal SEP interaction model adjustment covariates

	*NO_2 * Maternal Education*		*NO_2 * Medicaid Status*		*NO_2 * Maternal Ethnicity*	
Covariates	**Effect estimate (g)**	**95% CIs**	**Effect estimate (g)**	**95% CIs**	**Effect estimate (g)**	**95% CIs**
Intercept	2818.2	2767.9, 2868.4	2811.2	2780.3, 2842.1	2817.0	2784.2, 2849.8
Ethnicity						
US-born White [REF]	--	--	--	--	--	--
Foreign-born White	5.3	-1.6, 12.2	5.2	-1.7, 12.1	-24.4	-53.5, 4.7
US-born Black	-114.3	-121.8, -106.9	-114.4	-121.9, -107.0	-116.8	-152.1, -81.6
Foreign-born Black	-79.4	-87.1, -71.6	-79.4	-87.2, -71.7	-79.3	-118.3, -40.4
US-born Hispanic	-38.5	-45.8, -31.3	-38.7	-46.0, -31.5	-42.2	-75.8, -8.6
Foreign-born Hispanic	-1.8	-8.5, 4.9	-2.0	-8.7, 4.7	-14.0	-44.5, 16.5
US-born Asian	-105.0	-120.8, -89.1	-104.9	-120.8, -89.0	-116.0	-181.4, -50.7
Foreign-born Asian	-88.5	-95.4, -81.6	-88.7	-95.5, -81.8	-130.6	-160.1, -101.1
Maternal education						
< 9 yrs. [REF]	--	--	--	--	--	--
9 - 11 yrs.	-18.4	-66.6, 29.7	12.2	4.9, 19.5	12.1	4.8, 19.5
12 yrs. (High school)	-8.1	-54.1, 37.9	17.5	10.5, 24.6	17.4	10.3, 24.5
13 - 15 yrs.	37.0	-8.4, 82.4	34.7	27.3, 42.1	34.5	27.1, 42.0
16 yrs. (BA)	19.8	-25.3, 64.9	37.0	28.7, 45.4	37.1	28.7, 45.4
> 16 yrs.	26.6	-19.7, 72.8	36.3	27.1, 45.4	35.9	26.7, 45.0
Medicaid status						
No [REF]	--	--	--	--	--	--
Yes	1.4	-3.0, 5.9	-17.7	-37.4, 2.0	1.8	-2.7, 6.2
Maternal age (years)						
< 20 [REF]	--	--	--	--	--	--
20 - < 25	17.8	10.0, 25.6	17.8	10.0, 25.6	17.8	10.0, 25.6
25 - < 30	49.0	41.0, 57.1	49.0	41.0, 57.1	49.1	41.1, 57.2
30 - < 35	65.8	57.3, 74.3	65.8	57.3, 74.3	65.9	57.4, 74.4
35 - < 40	75.3	66.2, 84.5	75.4	66.3, 84.6	75.5	66.3, 84.6
≥ 40	62.4	51.0, 73.8	62.4	51.0, 73.8	62.6	51.2, 74.1
Pre-pregnancy BMI						
< 18.5 (Underweight) [REF]	--	--	--	--	--	--
18.5 - < 25 (Normal)	95.3	87.8, 102.8	95.3	87.8, 102.8	95.5	88.0, 103.0
25 - < 30 (Overweight)	159.7	151.6, 167.8	159.7	151.6, 167.7	159.9	151.8, 167.9
≥ 30 (Obese)	215.6	207.1, 224.1	215.5	207.0, 224.0	215.6	207.1, 224.1
Prenatal care received						
No [REF]	--	--	--	--	--	--
Yes	31.9	8.9, 55.0	32.0	8.9, 55.0	32.0	8.9, 55.0
Previous live births						
0 [REF]	--	--	--	--	--	--
1	68.4	64.3, 72.5	68.3	64.2, 72.4	68.4	64.3, 72.5
2	77.2	71.6, 82.8	77.1	71.6, 82.7	77.2	71.7, 82.8
≥ 3	76.8	70.1, 83.4	76.7	70.1, 83.4	76.7	70.0, 83.3
Gestational age (weeks)						
37 [REF]	--	--	--	--	--	--
38	198.8	191.7, 205.8	198.8	191.7, 205.8	198.7	191.7, 205.7
39	347.5	341.0, 354.0	347.5	341.0, 354.0	347.5	341.0, 354.0
40	454.8	448.1, 461.4	454.8	448.2, 461.5	454.7	448.1, 461.4
41	585.9	577.7, 594.1	585.9	577.7, 594.1	585.8	577.6, 594.0
42	648.4	627.5, 669.3	648.4	627.5, 669.4	648.3	627.4, 669.2

APPENDIX B: SPATIAL REGRESSION METHODS AND RESULTS

We explored multiple spatial statistical techniques accounting for spatial dependence in bivariate correlations, including Geographically Weighted Regression (GWR), Conditional Autoregressive (CAR), and selected Spatial (Simultaneous) Autoregressive (SAR) model as most appropriate to NYC administrative data, given irregular unit shape and size. Geographically Weighted Regression (GWR) allows regression coefficients to vary across space (i.e., non-stationarity); each observation (e.g., sampling point or areal unit) is the target of a separate regression spatially weighted against the entire domain (Fotheringham et al. 2002). GWR has greatest utility in multivariate models for which an inverse-distance weighting scheme is desirable (e.g., proximity analysis), and for research questions focusing on *locally-varying* predictor-outcome relationships. Conditional Autoregressive (CAR) and Spatial (Simultaneous) Autoregressive (SAR) models account for spatial autocorrelation *globally*, but CARs specify a symmetric covariance matrix. As such, spatial weights for CAR often include continuous inverse distance decay, not ideal for irregularly-shaped and -sized areal units (Goovaerts 2010; Kelsall and Wakefield 2002). Some analyses have reported negligible differences between SAR and CAR results (Wall 2004; Lichstein et al. 2002), but SAR requirements (e.g., flexible spatial weights definition, non-symmetric covariance) better match NYC administrative data.

SAR specification begins with diagnostic tests for spatial autocorrelation (i.e., Moran's I $p < 0.05$) on single-predictor Ordinary Least Squares (OLS) regression residuals. Autocorrelation among area-level measures may be caused by: 1) underlying social and/or chemical processes leading to inherent spatial clustering (e.g., higher air pollution concentrations closer to fixed sources), or 2) through "spill-over effects," a mismatch between the true scale of the underlying process and the administrative unit used (e.g., a neighborhood split across two Police Precincts).

To account for residual autocorrelation, SAR incorporates a *lag* (SAR_{lag}) or *error* (SAR_{err}) term (Anselin 2005; Anselin and Bera 1998). Generally, where residual autocorrelation is inherent in the predictor variable(s), SAR_{lag} models may be more appropriate, applying a weighted autoregressive term (*Wy*) to the response variable ($y = \rho Wy + x\beta + \varepsilon$, *with* $\varepsilon =$ is a vector of *iid* error terms). SAR_{err} models are useful when spatial dependence is observed primarily in residuals, and incorporate an autoregressive error term ($y = x\beta + \varepsilon$, with $\varepsilon = \lambda W \varepsilon + u$, a vector of spatially correlated error terms, and *u* is a vector of *iid* errors) (Kissing and Carl 2008; de Smith et al. accessed 2013). Having no *a priori* hypothesis about the nature of spatial processes operating across our multiple indicators, we assumed that different units and variables might give rise to diverse autocorrelation structures. As such, we referred to Lagrange Multiplier test statistics to specify SAR model-type (e.g., error or lag), following standard decision-making criteria [Anselin 2005, pp. 196-200].

Despite widespread univariate autocorrelation, relatively few (20%) bivariate comparisons called for SAR. As such, the main analysis prioritized comparability among r-values, and reported OLS Pearson rho values to estimate spatial correlation. Model fit was improved in all SAR models, measured by Log Likelihood Ratio test (Anselin 2005). SAR model-type was not patterned by administrative unit, or by stressor construct; 88% (n = 63) of comparisons called for an *error* model, versus a *lag* model (n = 9). Table 25 (next page) shows SAR pseudo-r-values, and illustrates the irregular nature of spatial dependence structures across units of aggregation and constructs. Though not directly comparable, all SAR pseudo-r-values were stronger than OLS r-values. The magnitude of that increase, however, varied substantially: among SAR_{err}, the mean difference was 0.34 (range 0.02 to 0.81), and among SAR_{lag}, the mean difference was on average less (mean=0.14, range 0.01 to 0.42), but also highly variable.

Importantly, SAR specification is determined jointly by all model covariates, and thus, multivariate epidemiological model specification depends on the underlying structures and spatial interactions present. The predominance of *error*, over *lag*, SAR models in this analysis may be a point of departure for spatial adjustment in complex multi-variable models moving forward. Spatial regression models are relatively new to environmental health research, and incorporating sensitivity tests for spatial autocorrelation in preliminary exploration and variable selection proved beneficial toward understanding SAR model specification.

Table 25. SAR pseudo-r-values and OLS Pearson rho, by stressor construct

	Larceny	Murder	Assault	Robbery	Burglary	Safety	Child abuse	Parks unclean	Sidewalks unclean	Serious housing violations	Air complaints	Crowding	No insurance	Without needed care	No medical provider	Public health insurance	Freq. noise disrupt	Traffic noise disrupt	Neighbor noise disrupt	Delayed rent/mortgage	Food Stamp enrollment	Less high school education	Unemployed	Poverty	% Non-White	% African American	% Hispanic
Larceny	1																										
Murder	-0.13	1																									
Assault	**0.64**	**0.68**	1																								
Robbery	0.33	**0.60**	**0.90**	1																							
Burglary	**0.90**	0.13	0.40	**0.62**	1																						
Safety	-0.33	**0.73**	**0.82**	**0.73**	-0.06	1																					
Child abuse	-0.02	**0.85**	**0.88**	**0.82**	-0.01	**0.85**	1																				
Parks unclean	-0.37	0.20	-0.38	0.02	-0.26	0.15	**-0.74**	1																			
Sidewalks unclean	-0.16	**0.83**	**0.86**	**0.81**	0.41	**0.76**	**0.86**	0.10	1																		
Housing Violations	-0.26	**0.66**	**0.71**	**0.62**	0.08	**0.84**	**0.67**	0.09	**0.74**	1																	
Air quality complaints	**0.84**	-0.34	-0.40	0.03	0.43	-0.52	**-0.77**	**-0.80**	-0.26	-0.36	1																
Crowding	-0.21	0.17	0.45	0.46	0.41	0.39	0.27	0.14	0.48	0.58	-0.20	1															
No insurance	-0.44	0.21	0.41	0.18	-0.41	0.51	0.28	0.30	0.38	0.50	-0.43	**0.63**	1														
Without care	-0.30	0.41	0.41	0.39	0.03	0.53	0.38	0.15	0.35	**0.63**	-0.29	0.34	0.50	1													
No provider	-0.03	0.09	0.22	0.22	0.09	0.44	0.15	-0.05	0.32	0.43	-0.03	**0.60**	**0.72**	0.22	1												
Public HI	-0.44	0.45	**0.68**	0.50	0.04	**0.70**	**0.74**	0.28	**0.69**	**0.63**	-0.52	**0.79**	0.56	0.37	0.46	1											
Freq. noise disruption	0.23	0.11	0.54	0.52	0.13	0.39	0.34	-0.06	0.24	0.30	0.22	0.33	0.23	0.25	0.24	0.39	1										
Traffic noise disruption	0.45	-0.19	0.14	0.18	0.10	-0.02	-0.11	-0.20	-0.01	-0.09	0.45	0.05	-0.03	-0.04	0.17	0.01	0.73	1									
Neighbor noise disruption	-0.28	0.50	0.47	0.26	-0.06	0.56	0.53	0.36	0.47	0.51	-0.31	0.41	0.41	0.26	0.18	0.52	0.42	0.01	1								
Delayed rent	-0.37	**0.67**	**0.74**	**0.60**	0.38	**0.82**	**0.73**	0.52	0.28	0.81	-0.54	0.53	**0.62**	0.56	**0.60**	**0.67**	0.41	-0.32	**0.64**	1							
Food Stamp enrollment	-0.27	**0.66**	**0.82**	**0.85**	0.10	**0.84**	**0.95**	**0.69**	**0.87**	**0.74**	-0.38	0.46	0.36	0.40	0.26	**0.88**	0.42	-0.02	0.52	**0.70**	1						
% Less high school	-0.25	0.31	0.49	0.49	0.14	**0.66**	0.52	0.04	0.52	**0.61**	-0.28	**0.83**	0.55	0.49	0.55	**0.80**	0.36	0.04	0.31	**0.63**	**0.62**	1					
% Unemployed	0.20	0.39	0.52	0.48	0.3	**0.83**	0.36	0	0.35	0.42	0.04	0.28	0.41	0.46	**0.73**	0.21	0.40	0.08	0.33	**0.63**	0.31	0.46	1				
% <200% FPL	-0.08	0.51	**0.72**	**0.60**	-0.03	**0.75**	**0.78**	0.19	**0.80**	**0.80**	-0.40	**0.79**	0.57	0.42	0.52	**0.92**	0.57	0.18	0.55	0.63	0.91	0.80	0.28	1			
% Non-White	-0.34	**0.64**	**0.72**	0.58	-0.01	**0.79**	**0.71**	0.10	0.50	**0.72**	-0.52	0.37	0.50	0.59	0.44	**0.70**	0.20	0.14	0.30	**0.77**	**0.73**	**0.60**	0.36	0.55	1		
% African American	-0.21	**0.75**	0.55	0.52	-0.02	0.59	0.48	0.15	0.51	0.49	-0.35	0.08	0.17	0.48	0.02	0.24	0	0.25	0.30	**0.68**	0.49	0.11	0.32	0.16	**0.70**	1	
% Hispanic	-0.25	0.14	0.40	0.35	-0.10	0.59	**0.63**	0.01	0.27	**0.63**	-0.32	**0.60**	0.49	0.39	0.55	**0.70**	0.34	0.06	0.24	0.47	**0.64**	0.76	0.20	**0.63**	0.57	-0.06	1

* Bold values indicate rho ≥ 0.60. Shaded areas indicate SAR pseudo-r-values (grey = SAR error model, blue = SAR lag model).

APPENDIX C: FOCUS GROUP MODERATOR'S GUIDE

1. INTRODUCTION AND PURPOSE (approx. 2 minutes)

Good afternoon/ Good evening. My name is [ ]. I'll be the moderator for today's 60 minute focus group discussion. Thank you so much for coming.

We are here today to talk about the neighborhood where you live. The primary goal of our conversation is to identify and describe key characteristics and conditions of diverse New York City neighborhoods.

Throughout our discussion, I will be referring to my notes to be sure we cover all the topic areas of importance. Please understand that there are no right or wrong answers, and you will not be judged for your opinions or ideas. You should feel free to make negative or positive comments. We just ask that you share with us how you honestly feel, and that you respect the opinions of others in the room.

<< Note to Moderator: Everything in *Italics* should be read verbatim. >>

2. DISCLOSURES AND GROUND RULES (approx. 3 minutes)

The consent form you signed provided you information about confidentiality and participation, but I want to review a few key items briefly before we begin:

CONFIDENTIALITY: *First, in the interest of privacy, we ask that everything said here be kept strictly confidential. By participating, you are agreeing to not share the comments, perspectives, and identity of others in the room, after you leave. Second, during this conversation, please do not disclose personal information or experiences about yourself or others. Please try to describe the opinions of people living in your neighborhood, rather than your specific personal experience.*

VOLUNTARY PARTICIPATION: *Your participation in this group is entirely voluntary. You don't have to answer any questions that you don't want to, and you may withdraw from the group at any time.*

NOTETAKING AND AUDIOTAPING: *We will be taking notes and the discussion will be audio taped. This is only to ensure that we don't miss anything said, and can write an accurate report. No names or identifying information will be associated with what is discussed here today. We respect your right to privacy, and will not share this information with anyone outside of our evaluation team.*

GROUND RULES (Also posted on wall):

1. *This is a group discussion, so feel free to respond to me and/or to other group members.*
2. *Please talk one at a time, loud enough for everyone to hear and for the audiotape to pick up.*
3. *While it's difficult for some people to speak up in a group setting, you have been invited here tonight because we value each of your perspectives and opinions. We want to hear from everyone during this focus group, so please actively participate, and please allow others to freely express their own opinions.*
4. *Please be honest! You all have valuable insights, and we want to hear about them.*
5. *And again, please do not share sensitive, personal information either about yourself or those you know. Answers to specific questions should be communicated from the perspective of "people living in your neighborhood."*

QUESTIONS: *Does anyone have any questions before we begin?*

3. PARTICIPANT INTRODUCTIONS (approx. 3 minutes)

Let's start with introductions. Let's go around the room, and introduce ourselves by first name only. Please share with us one of the most positive experiences you've had in your lifetime.

4. FOCUSED DISCUSSION

We will be gathered here for about an hour, and we have a lot to cover, so at times I may need to steer us along to the next topic. Please don't be offended if I need to redirect you at any point.

Your neighborhood (12 minutes): *To get us started, recall the mapping exercise we asked you to complete before this discussion. Let's start by talking about how we each defined our neighborhood. So, how would you define the neighborhood where you live?*

<u>Probes (to be used sparingly)</u>:

- Does it have physical boundaries? Social boundaries?
- Is your "neighborhood" the same thing as your "community"? If not, how are they different?
- Do you think of your neighborhood as home? Why or why not?
- Generally speaking, do you think people in your neighborhood <u>choose</u> to live where they do? If so, for what reasons?
- Do you think people enjoy living in your neighborhood?

For the rest of our time together, we are going to refer to neighborhoods – meaning the people, homes, businesses, parks, and other locations around the place where you live.

Positive Attributes of Your Neighborhood (10 minutes): *Now I'll ask each of you to think about the neighborhood you've just described, and consider its most positive aspects. Please share what you believe are your neighborhood's best qualities. Please be as specific as you can, and consider any of the physical, social, or political aspects of your neighborhood.*

<u>Note to Moderator:</u> As participants name positive attributes, write them on a blank index cards and tape it to the wall. Focus here on positive environmental attributes. If a negative attribute comes up, write it on a blank index card and "table" it. When the conversation about stressors in the next section begins, tape these stressors to the wall.

Probes (to be used sparingly):

- What resources does your neighborhood have? Or key services?
- Do you feel that people in your neighborhood have easy access to these resources?
- How important do you think these resources are to your neighbors?
- How do you think the presence (or absence) of these attributes or resources affect the people who live in your neighborhood?
- Would you describe your neighborhood as one where people have a strong sense of community—or where people regularly come together to create positive change (i.e.: is there a strong religious presence)?

Summarize responses:

OK, that's a great list. Read aloud the positive attribute index cards taped to the wall.

Anything else we haven't mentioned?

Negative or Stressful Attributes of Your Neighborhood: *Now let's talk about the less positive aspects of your neighborhood. Let's hear about the aspects of your neighborhood that might be considered less than ideal.*

First, let's talk about the physical environment. **(10 minutes)**

Note to Moderator: Start by removing the positive index cards, and taping up the "tabled" stressor index cards on the opposite side of the wall. Let respondents offer ideas spontaneously, and capture on index cards, as above. Begin to cluster similar or related challenges together as the conversation proceeds. Focus the discussion around physical stressors. Social/emotional stressors will be discussed in the next section.

Probes (to be used sparingly):

- If you could change anything about the physical environment of your neighborhood, what would it be?
- How would you describe the quality of public spaces in your neighborhood (schools, libraries, medical facilities, green spaces, etc.)?
- How about the private spaces (such as restaurants, churches, private homes)?

- Is your neighborhood anything that you or your neighbors might consider dirty, loud unpleasant, or disruptive?
- How about public services?
- Is transportation is an issue for your community? Pest problems?

Summarize responses:

OK, that's a great list. Read aloud the attribute index cards taped to the wall.

Anything else we haven't mentioned?

***Now let's talk about the social aspects that people living in your neighborhood might consider problematic* (10 minutes).** *What are some of the less desirable aspects of your neighborhood, related to social life and peace of mind? If you could change anything about the social environment in which you live, what would it be?*

Note to moderator: As above, let respondents offer ideas spontaneously, and capture stressors on index cards. Some physical stressors (e.g., availability of green space), can have a social/emotional component, so may refer to physical stressors above, as appropriate.

Probes (use sparingly):

- Do you think people in your neighborhood generally feel safe?
- Do neighbors generally try to help each other?
- Do people generally trust their neighbors?
- What about education, healthcare or childcare?
- Are people aggressive towards each other in your neighborhood?

Summarize responses:

OK, that's a great list. Read aloud the attribute index cards taped to the wall.

Anything else we haven't mentioned?

5. VOTING EXCERSIZE (10 minutes)

Finally, I am going to give each of you a set of sticker dots: 5 big ones and some small ones. Let's start with the small *dots. Please come up to the front of the room and review the items on the wall. Please place one* small dots *on EACH issue that you believe people in your neighborhood find stressful. Use only one small dot per item. You do not need to use all your dots.*

Now, please consider all the items you placed a small dot on. Please identify up to 5 things you think people in your neighborhood find the MOST stressful. Place your large dots *next to these items. You may place as many dots as you wish on each item.*

6. CLOSING (approx. 5 minutes)

Ask respondents to be seated again for the wrap-up.

- *What do we observe in the patterns of dots?*
- *Is the pattern what we expected? Anything surprising?*
- *Is there anything else regarding neighborhood conditions that we did not discuss that you think would be useful for us to know?*

Thank you so much for coming! Your time is so appreciated and your comments will be extremely helpful in learning more about neighborhood well-being.

We would appreciate your feedback on how we can improve focus groups. Here is a short evaluation form.

Collect evaluation forms.

APPENDIX D: LAY POSTER - COMMUNITY DISSEMINATION OF FOCUS GROUP RESULTS

To communicate study findings to community residents, we developed a lay poster describing the study and neighborhood stressors themes identified through focus group discussions (next page). Posters were distributed by WE ACT to CBOs who participated in recruitment and/ or hosted focus groups, as well as other CBOs in WE ACT's extended NYC network.

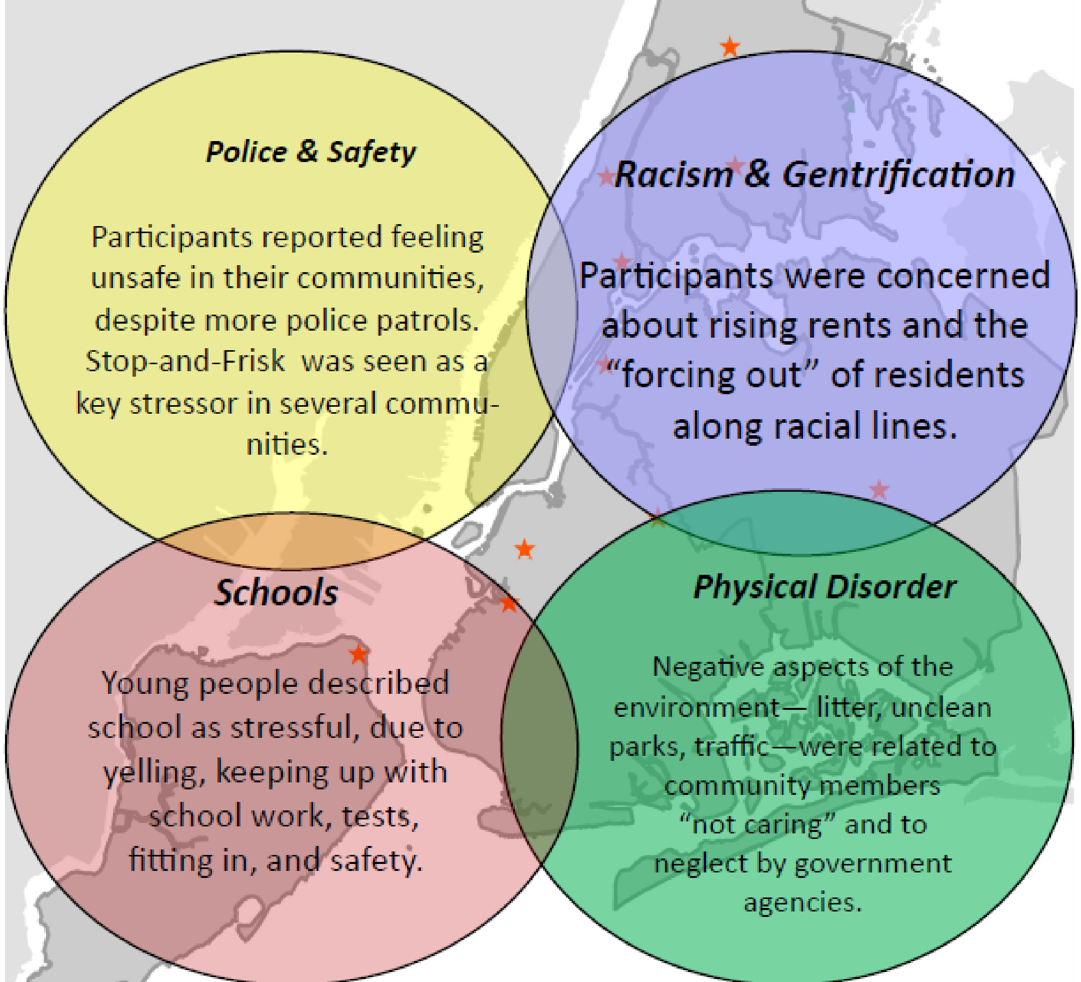
What community stressors are important to New Yorkers?
Results of a Focus Group Research Study

What are stressors?
Neighborhood characteristics that may cause emotional distress to residents, such as crime, noise, or lack of access to resources.

We used focus groups to understand which stressors are important to residents of NYC neighborhoods.
We are interested in community stressors because, over time, repeated stressful experiences might increase our bodies' susceptibility — our ability to heal, to fight infection, or our resilience to everyday pollution exposures — potentially increasing our risk of disease. This theory is called *allostatic load*.

Who participated in focus groups?
Community members from all 5 boroughs, Spanish and English speakers, adults and young people (aged 15-18).

What stressors were identified through community focus groups?



How do we use information from focus groups in health research?
The stressors identified were used to design a detailed citywide survey. Over the next 2 years, this survey will inform a larger study on chronic stress, air pollution, and childhood asthma across NYC.

Who are the researchers?
We are environmental justice advocates and public health researchers from WE ACT for Environmental Justice (Harlem, NY) and the University of Pittsburgh (Pittsburgh, PA).

This work is funded by the U.S. Environmental Protection Agency (EPA).

For more information please contact:
Ogonnaya Dotson-Newman, Director of Environmental Health, WE ACT
P: (212) 961-1000 ext 310; Email: ogonnaya@weact.org

APPENDIX E: ONLINE NEIGHBORHOOD MAPPING SURVEY

Study introduction and informed consent:

This brief questionnaire will help us better understand how people perceive the size and shape of their "neighborhoods," and how this perceived neighborhood scale may differ across the city.

If you choose to participate, we will ask about your neighborhood and your background (e.g., age, race, education). There are no foreseeable risks associated with this project, nor any direct benefits. This is an entirely anonymous questionnaire, and so your responses will not be identifiable in any way. All responses are confidential, and results will be kept under lock and key. Your participation is voluntary, and you may withdraw from the study at any time.

Instructions:

This survey should take about 10 minutes to complete. If you get interrupted while taking this survey, you can save your responses and continue at a later time by clicking the «Save & Return Later» button located at the bottom of most pages. When you are finished with this survey it is very important that you submit your responses by clicking the «Submit My Responses» button located on the very last page.

Neighborhood Questionnaire:

1. What city do you live in? ______________________________

1 ☐ New York City   2 ☐ Pittsburgh

2. What neighborhood do you live in? ____

3. How long have you lived in the neighborhood?

1 ☐ Less than 1 year 2 ☐ 1 to 5 years   3 ☐ 6 to 10 years
4 ☐ More than 10 years

4. What are the nearest cross-streets (intersection) to your home?

(Please do NOT write your home address.)

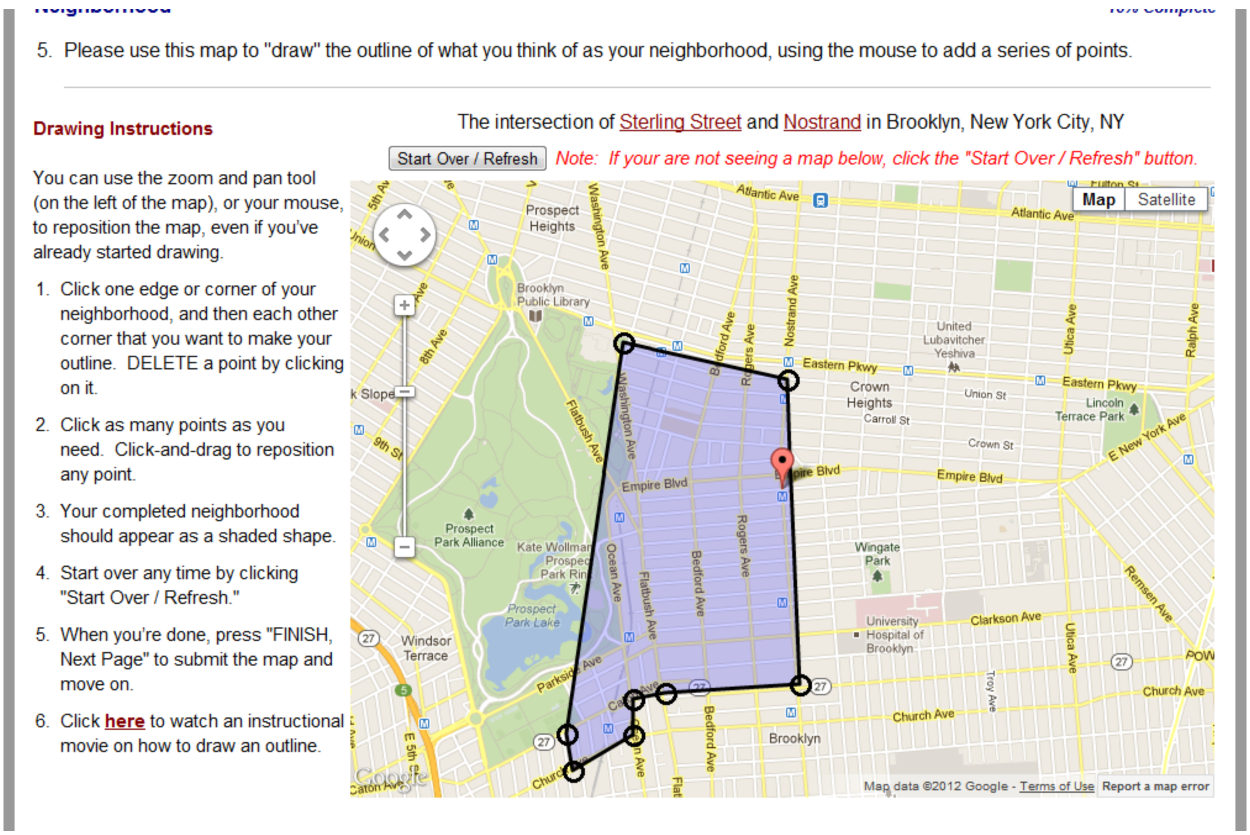
____

____

<Previously supplied city and nearest cross-streets drive Google.Maps to pre-defined 3 mile^2 extent, centered on cross-streets.>

5. Please use this map to "draw" the outline of what you think of as your neighborhood, using the mouse to add a series of points.

<screen shot of mapping interface and completed neighborhood polygon>



6. How did you decide where to draw the lines around your neighborhood?

________________________________ (*open-response*)

7. Which streets, avenues, or parks outline your neighborhood?

________________________________ (*3 to 5 open-response fields*)

8. How <u>useful</u> were the mapping instructions that were located on the left side of the screen?

1 ☐ Very useful 2 ☐ Somewhat useful 3 ☐ Not at all useful
4 ☐ I did not read the instructions

9. How <u>useful</u> was the instructional movie?

1 ☐ Very useful 2 ☐ Somewhat useful 3 ☐ Not at all useful
4 ☐ I did not watch the instructional video

10. How <u>easy</u> was it for you to draw the outline of your neighborhood?

1 ☐ Very easy 2 ☐ Somewhat easy 3 ☐ Not at all easy

11. <u>How accurate</u> do you think the map was for drawing the outline of your neighborhood?

1 ☐ Very accurate 2 ☐ Somewhat accurate 3 ☐ Not at all accurate

12. About how much of your time is spent in your neighborhood on <u>weekdays</u>?

1 ☐ almost none 2 ☐ some 3 ☐ most 4 ☐ all

13. About how much of your time is spent in your neighborhood on <u>weekends</u>?

1 ☐ almost none 2 ☐ some 3 ☐ most 4 ☐ all

14. Which of your day-to-day activities occur <u>within</u> your neighborhood? [*Activities may include: grocery shopping, work, errands, day care, visiting with family/friends, sports/recreation, community/faith-based activities, etc*.]

____ (*up to 15 open=response fields*)

15. For which activities or services must you travel <u>outside</u> of your neighborhood?

____ (*up to 15 open-response fields*)

Demographic Information:

15. What is your approximate household income?

1 ☐ Less than $23,000
2 ☐ $23,000 – $46,000
3 ☐ $46,000 – $70,000
4 ☐ $70,000 – $93,000
5 ☐ $93,000 – $135,000
6 ☐ $135,000 – $160,000
7 ☐ More than $160,000

16. What is the highest level of school you have completed?

1 ☐ Less than fifth grade
2 ☐ Fifth grade to eighth grade
3 ☐ Junior High School (9^{th} grade)
4 ☐ Partial High School ($10\text{-}11^{th}$ grade)
5 ☐ High School graduate
6 ☐ Partial College
7 ☐ Completed College
8 ☐ Graduate School

17. Age: ______

18. Sex: 1 ☐ Male 2 ☐ Female

19. Are you of Hispanic, Latino or Spanish origin?

1 ☐ No

2 ☐ Yes, Mexican, Mexican American, or Chicano

3 ☐ Yes, Puerto Rican

4 ☐ Yes, Dominican

5 ☐ Yes, other Hispanic, Latino or Spanish origin (Please print origin, for example “Nicaraguan.”) ________________________

20. Race – You make check more than one box:

1 ☐ American Indian or Alaska Native

2 ☐ Asian/ Pacific Islander

3 ☐ Black/ African American

4 ☐ White

5 ☐ Other ________________________________

APPENDIX F: SURVEY QUESTIONNAIRE

Contents:

1. Introductory script; spatial allocation screen
2. Demographic information (13 items)
3. Neighborhood mapping (5 items RDD; 6 items online)
4. Asthma information (1-6 items)
5. Social capital & Social cohesion (7 items)
6. Perceived Stress Scale (4 item version)
7. Ross-Mirowsky Perceived Neighborhood Disorder Scale (16 items)
8. Perceived Neighborhood Air Quality (3 items)
9. CES-D Depression scale (10 items)
10. MMPI Anxiety Scale (23 items)
11. MacArthur Ladder (2 items)
12. Spielberger Trait Anger Expression Inventory (10 items)
13. General & Mental Health (3 items)
14. Neighborhood Violence (8 items)
15. Individual social support and resources (14 items)
16. Everyday Unfair Treatment (short version = 6 items)
17. Life Events (14 items)
18. Sandy questions (Winter wave only)

INTRODUCTION SCRIPT

Hello, My name is _________________, and I am calling on behalf of the University of Pittsburgh Graduate School of Public Health. We're conducting an important study to understand stress among New Yorkers. You have been selected as a representative of your Borough. (If they ask how selected, random digit dial process.)

All answers you give will be confidential. You don't have to give me any personal identifying information such as your full name or address.

This survey will take approximately 15-20 minutes, and to say thank you for so generously giving your time we will send you a $5 gift card to Dunkin Doughnuts.

Spatial allocation screen:
What Borough do you live in?

1. Bronx
2. Manhattan
3. Queens
4. Brooklyn
5. Staten Island

DEMOGRAPHIC INFORMATION

INTERVIEWER: *I'm going to start by asking you some general questions about your neighborhood and background.*

1. Age: ______

2. Sex: 1 ☐ Male 2 ☐ Female

3. Ethnicity: 1 ☐ Hispanic/ Latino 2 ☐ NOT Hispanic/ Latino

4. Race: *race*
   1 ☐ White/ Caucasian
   2 ☐ Black/ African American
   3 ☐ Asian/ Pacific
   4 ☐ Native American
   5 ☐ Other ______________________________________

5. Marital Status:
   1 ☐ Married/living as married
   2 ☐ Separated
   3 ☐ Divorced
   4 ☐ Widowed
   5 ☐ Single, never married

6 Which one of the following BEST describes your employment status?

01. Employed full-time
02. Employed part-time
03. Self-employed
04. Out of work and looking for work
05. Out of work but not currently looking for work
06. A homemaker
07. A student
08. Retired
09. Unable to work

7. Occupation: ____

8. What kind of health insurance do you have? (CHECK ALL THAT APPLY)

01. Private
02. Medicare
03. Medicaid
04. Self-pay
05. Other (SPECIFY)
06. No Insurance

9. Education: Highest level of school you have completed?

01. Eighth grade or less
02. Some high school
03. High school graduate or GED
04. Trade / vocational / nursing school
05. Some college, no degree
06. Associate's degree
07. Bachelor's degree
08. Master's degree
09. Professional degree
10. Doctoral degree

10. What is your estimated annual household income?

1 ☐ Less than $23,000
2 ☐ $23,000 – $46,000
3 ☐ $46,000 – $70,000
4 ☐ $70,000 – $93,000
5 ☐ $93,000 – $135,000

NEIGHBORHOOD INFORMATION

1. What neighborhood do you live in? ____________________________________

2. How long have you lived in the neighborhood?

1 ☐ Less than 1 Year

2 ☐ 1-5 years

3 ☐ 5-10 years

4 ☐ More than 10 years

3. What are the nearest cross-streets (intersection) to your home?

(Please do NOT state your home address.)

____

4. What is your residential zip code? _______

INTERVIEWER: *Finally, I'll ask a few questions about the geography of your neighborhood.*

5. When you think of the space you would consider "your neighborhood", which streets, avenues, or parks outline your neighborhood? By neighborhood we mean the area around where you live, not just your apartment or house. Please do not mark your address on the map.

__________________________ *bound1*

__________________________ *bound2*

__________________________ *bound3*

__________________________ *bound4*

<<Online frame only>>

6. Please draw the outline of the area you consider your neighborhood.

ASTHMA INFORMATION[1]

INTERVIEWER: Next, I'll ask some questions about your health and asthma.

1. Have you ever been told by a healthcare provider that **you** have asthma?

1 ☐ Yes 0 ☐ No

2. Do any children (under age 18) live in your home, at least half the time? [for skip logic]

1 ☐ Yes 0 ☐ No

[If NO to Question 2 AND YES to Question 1, skip to Question 6 and ask only for "you"]

3. How many children (under age 18) live in your home, at least half the time?

1 ☐ 1 2 ☐ 2 3 ☐ 3 4 ☐ 4 or more

[Assign each child a number for the remainder of questions (e.g., oldest = 1, second oldest = 2, etc. Do not record child's name. Repeat this series for as many children as live in the home of respondent.]

Shortened* ISAAC Asthma Questionnaire:

4.	How many attacks of wheezing or asthma has your child had **in the last 6 months**? 0 ☐ None 1 ☐1 to 3 2 ☐ 4 to 12 3 ☐ More than 12
5.	Has your child ever been told they have asthma by a doctor or nurse? 1 ☐ Yes 0 ☐ No
6.	In the last 6 months, did ***you or your child*** miss school or work due to asthma? 1 ☐ Yes 0 ☐ No

* retained 2 of original 8, and added Q6.

[1] Asher MI, Keil U, Anderson HR, Beasley R, Crane J, Martinez F, Mitchel EA, Pearce N, Sibbald B, Stewart AW, Strachan D, Weiland SK, Williams HC. 1995. International study of asthma and allergies in childhood (ISAAC): rationale and methods. Eur Respir J 8:483-491.

SOCIAL CAPITAL & SOCIAL COHESION[2]

INTERVIEWER: Next, I'll read you a series of statements about your neighborhood, and you can: strongly agree, agree, disagree, strongly disagree, or say you don't know. There are no wrong answers.

This is a close-knit neighborhood [rev score]

People in this neighborhood can be trusted [rev score]

People in this neighborhood don't share the same values

I feel like I belong around here [rev score]

I enjoy living around here [rev score]

Given the opportunity, I would like to move away from here

I think this is a good place to bring up children [rev score]

RESPONSE OPTIONS:
Strongly Disagree
Disagree
Agree
Strongly Agree
Don't Know

Note: positively phrased statements must be reverse coded for interpretation [rev score]

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[2] **Q1-3:** Adapted from Neighborhood Social Capital scale from the Project on Human Development in Chicago Neighborhoods (3 of original 5 items retained)

Sampson RJ, Rauderbush SW, Earls F. 1997. Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. Science 277:918-924. Scale available: http://coglab.wjh.harvard.edu/soc/faculty/sampson/articles/1997_Science.pdf

Q4-7: Adapted from the Perceptions of Social Capital and Built Environment in South Wales scale (4 of original 7 items retained)

Araya R, Dunstan F, Playle R, Thomas H, Palmer S, Lewis G. 2006. Perceptions of social capital and the built environment and mental health. Soc Sci Med 62:3072–3083.

COHEN PERCEIVED STRESS SCALE (4-item version)[3]

INTERVIEWER: Now I'll ask some questions about your feelings and thoughts **during the last month**.

	Never	Almost Never	Sometimes	Fairly Often	Very Often
In the **last month**, how often have you felt that you were unable to control the important things in your life?	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
In the **last month**, how often have you felt confident about your ability to handle your personal problems?	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
In the **last month**, how often have you felt that things were going your way?	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐
In the **last month**, how often have you felt difficulties were piling up so high that you could not overcome them?	0 ☐	1 ☐	2 ☐	3 ☐	4 ☐

INTERVIEWER: *IF PARTICIPANT ANSWERS AFFIRMATIVELY TO ANY QUESTIONS IN THE ABOVE MENTAL HEALTH SCALES OR ASKS FOR HELP WITH MENTAL HEALTH, PLEASE PROVIDE THE TOLL-FREE NUMBER FOR NYC DOHMH LIFENET:*

- *ENGLISH LIFENET: 1-800-LIFENET (543-3638).*
- *SPANISH LIFENET: 1-877-AYUDESE (298-3373)*
- *ASIAN LANGUAGE LIFENET: 1-877-990-8585*
- *DEAF/HEARING IMPAIRED: 212-982-5284*

INTERVIEWERS WILL BE PROVIDE THIS PDF OF THE LIFENET BROCHURE FOR MORE INFORMATION ON FREE NYC MENTAL HEALTH TREATMENT AND SCREENING RESOURCES: http://www.nyc.gov/html/doh/downloads/pdf/dmh/dmh-lifenet-brochure.pdf

[3] Cohen S, Kamarck T, Mermelstein R. 1983. A global measure of perceived stress. J Health Soc Behav 24:385-396. 4-item scale available: http://www.psy.cmu.edu/~scohen/PSS4.html

NEIGHBORHOOD PHYSICAL AND SOCIAL DISORDER[4]

INTERVIEWER: *Next, I'll read you a series of statements about the physical and social conditions in your neighborhood, and you can: strongly disagree, disagree, agree, strongly agree, or say you don't know. There are no wrong answers.*

1. My neighborhood is clean [rev score]
2. Houses and apartments in my neighborhood are well taken care of [rev score]
3. There are too many people hanging around on the streets near my home
4. There is a lot of crime in my neighborhood
5. There is too much drug use in my neighborhood
6. There is too much alcohol use in my neighborhood
7. I'm always having trouble with my neighbors
8. In my neighborhood, people watch out for each other [rev score]
9. My neighborhood is safe [rev score]
10. Rats and vermin are common in my neighborhood *****
11. Public transportation serves my neighborhood well [rev score] *****
12. The police presence in my neighborhood is more beneficial than stressful [rev score] *****
13. There are lots of abandoned buildings in my neighborhood
14. Vandalism is common in my neighborhood
15. My neighborhood is noisy
16. There is a lot of graffiti in my neighborhood

RESPONSE OPTIONS:

1. Strongly Disagree
2. Disagree
3. Agree
4. Strongly Agree
5. Don't Know

Note: positively phrased statements must be reverse coded for interpretation [rev score]

***** Items added based on community-reported important neighborhood stressors (Shmool et al. *under review).*

[4] Ross C E, Mirowsky J. 2001. Neighborhood Disadvantage, Disorder, and Health. J Health Soc Behav 42(3):258-276.

PERCEIVED NEIGHBORHOOD AIR QUALITY

1. The air in my neighborhood seems worse than in other neighborhoods.
2. I am bothered by pollution from cars, trucks, or buses in my neighborhood.
3. I am bothered by air pollution from industry or other pollution sources in my neighborhood.

RESPONSE OPTIONS:

1. Strongly Disagree
2. Disagree
3. Agree
4. Strongly Agree
5. Don’t Know

CES-D DEPRESSION[5]

<u>INTERVIEWER</u>: *The following questions ask about your feelings during the **past week**.*

	NEVER	RARELY	SOMETIMES	FAIRLY OFTEN	VERY OFTEN
1. I was bothered by things that usually don't bother me	☐	☐	☐	☐	☐
2. I had trouble keeping my mind on what I was doing	☐	☐	☐	☐	☐
3. I felt depressed	☐	☐	☐	☐	☐
4. I felt that everything I did was an effort	☐	☐	☐	☐	☐
5. I felt hopeful about the future [rev score]	☐	☐	☐	☐	☐
6. I felt fearful	☐	☐	☐	☐	☐
7. My sleep was restless	☐	☐	☐	☐	☐
8. I was happy [rev score]	☐	☐	☐	☐	☐
9. I felt lonely	☐	☐	☐	☐	☐
10. I could not "get going"	☐	☐	☐	☐	☐

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Note: positively phrased statements must be reverse coded for interpretation [rev score].

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5 Radloff LS. 1977. The CES-D scale: A self-report depression scale for research in the general population. Applied Psychological Measurement 1:385-401.

Irwin M, Artin KH, Oxman MN. 1999. Screening depression in the older adult: criterion validity of the 10-item Center for Epidemiological Stidues Depression Scale (CES-D). Arch Intern Med 159:1701-1704.

MMPI ANXIETY SCALE[6]

INTERVIEWER: *I am going to read to you a number of statements that people have used to describe themselves. Please indicate the extent to which each statement applies to you: rarely or none of the time, some or little of the time, moderate amount of time, or most of the time. There is no right or wrong answer. You don't need to spend too much time on any one statement, but give the answer that seems to describe you best.*

		Rarely or none of the time	Some or little of the time	Moderate amount of time	Most or all of the time
1.	I work under a great deal of tension	1	2	3	4
2.	I have nightmares every few nights	1	2	3	4
3.	I believe I am no more nervous than most others [rev score]	1	2	3	4
4.	I find it hard to keep my mind on a task or job	1	2	3	4
5.	Several times a week I feel as if something dreadful is about to happen	1	2	3	4
6.	I worry over money and business	1	2	3	4
7.	Life is a strain for me much of the time	1	2	3	4
8.	Most nights I go to sleep without thoughts or ideas bothering me [rev score]	1	2	3	4
9.	I cannot keep my mind on one thing	1	2	3	4
10.	I feel anxiety about something or someone almost all of the time	1	2	3	4
11.	Having to make important decisions makes me nervous	1	2	3	4
12.	I am not feeling much pressure or stress [rev score]	1	2	3	4
13.	I am apt to take disappointments so keenly that I can't put them out of my mind	1	2	3	4
14.	I worry quite a bit over possible misfortunes	1	2	3	4
15.	I have sometimes felt that difficulties were piling up so high that I could not overcome them	1	2	3	4
16.	I worry a great deal over money	1	2	3	4
17.	My sleep is fitful and disturbed	1	2	3	4
18.	I sometimes feel that I am about to go to pieces	1	2	3	4
19.	I hardly ever notice my heart pounding and I am seldom short of breath [rev score]	1	2	3	4
20.	I frequently find myself worrying about something	1	2	3	4
21.	I am afraid of losing my mind	1	2	3	4
22.	I am usually calm and not easily upset [rev score]	1	2	3	4
23.	I have certainly had more than my share of things to worry about	1	2	3	4

[6] Butcher JN, Dahlstrom WG, Graham JR, Tellegen A, & Kaemmer B. *MMPI-2: Minnesota Multiphasic Personality Inventory-2. Manual for administration and scoring*. Minneapolis, MN: University of Minnesota Press: 1989.

MACARTHUR LADDER[7]

INTERVIEWER: *Next, I'd like to ask a couple questions about your social standing, meaning your education, wealth, respect, power. On a scale of 1 to 7, with highest social standing ranked 7 and lowest standing ranked 1:*

1. Where do you think you stand at this time in your life relative to the rest of New York City residents?

7☐	6☐	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐

2. Where do you think you stand at this time in your life relative to your neighborhood?

7☐	6☐	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐

[Note: For online survey, the ladder visual can be used with number labeled rungs.]

Think of this ladder as representing where people stand in their communities.

People define community in different ways; please define it in whatever way is most meaningful to you. At the **top** of the ladder are the people who have the highest standing in their community. At the **bottom** are the people who have the lowest standing in their community.

Where would you place yourself on this ladder?

Please place a large "**X**" on the rung where you think you stand at this time in your life, relative to other people in your community.

[7] MacArthur Research Network on SES & Health. "The MacArthur Scale of Subjective Social Status." University of California, San Francisco. Available: http://www.macses.ucsf.edu/research/psychosocial/subjective.php

TRAIT ANGER[8]

INTERVIEWER*: I am now going to read you several statements that people have used to describe how they generally feel or react, whether it is almost never, sometimes, often, or almost always. There are no right or wrong answers.*

1. I am quick tempered.
2. I have a fiery temper
3. I am a hotheaded person
4. I get angry when I'm slowed down by other' mistakes
5. I fly off the handle
6. I feel annoyed when I am not given recognition for doing good work
7. When I get mad, I say nasty things
8. It makes me furious when I am criticized in front of others
9. When I get frustrated, I feel like hitting someone
10. I feel infuriated when I do a good job and get a poor evaluation

RESPONSE OPTIONS

1. Rarely
2. Some or little of the time
3. Moderate amount of the time
4. Most or all of the time

INTERVIEWER: *IF PARTICIPANT ANSWERS AFFIRMATIVELY TO ANY QUESTIONS IN THE BELOW MENTAL HEALTH SCALES OR ASKS FOR HELP WITH MENTAL HEALTH, PLEASE PROVIDE THE TOLL-FREE NUMBER FOR NYC DOHMH LIFENET:*

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- *ASIAN LANGUAGE LIFENET: 1-877-990-8585*
- *DEAF/HEARING IMPAIRED: 212-982-5284*

[8] Spielberger CD, Reheiser EC, Sydeman SJ. 1995. Measuring the experience, expression, and control of anger.In H. Kassinove (Ed.), In: *Anger disorders: Definition, diagnosis, and treatment* (pp. 49-67). Washington, DC: Taylor & Francis.

GENERAL & MENTAL HEALTH[9]

<u>INTERVIEWER</u>: *Now I'm going to ask you a few questions about your general and mental health.*

1. Would you say that in general your health is excellent, very good, good, fair or poor?

1 EXCELLENT

2 VERY GOOD

3 GOOD

4 FAIR

5 POOR

7 DON'T KNOW/NOT SURE

2. During the **past year**,[10] have you received any counseling or taken prescription medication for your mental health?

1 ☐ Yes   0 ☐ No

3. Have you **ever been told** by a doctor, nurse or other health professional that you have depression?

1 ☐ Yes   0 ☐ No

[9] Department of Health and Mental Hygiene (NYC DOHMH). 2009 Community Health Survey Questionnaire. Available: http://www.nyc.gov/html/doh/downloads/pdf/episrv/chs2009survey.pdf

Q2-3: Modified from "past 30 days" to "past year."

NEIGHBORHOOD VIOLENCE[11]

*INTERVIWER: Now, I'll ask you some yes/no questions about violent events in your neighborhood during the **past 6 months**. You can also answer that you don't know.*

1. Are you afraid you or your children will be hurt by violence in your neighborhood?

(1) [ ] Yes

(2) [ ] No

(9) [ ] Don't know

2. While you have lived in this neighborhood, has anyone used violence against you or any member of your household anywhere in your neighborhood?

(1) [ ] Yes

(2) [ ] No

(9) [ ] Don't know

3. [skip logic – only ask if answered Yes to "Children living in the house…"] Do you not let your children play outside because you are afraid they might be hurt by violence in the neighborhood?

(1) [ ] Yes

(2) [ ] No

(9) [ ] Don't know

4. Did any of the following occur to your knowledge in your neighborhood during the past **6 MONTHS**?

(INTERVIEWER: IF THE ANSWER TO THE FIRST QUESTION IS "No", SKIP THE "More than Once" QUESTION. IF THE ANSWER IS "I don't know", RECORD AS "No")

5a. A fight in which a weapon was used?	(1)	[ ]	Yes	(2)	[ ]	No
5b. More than once?	(1)	[ ]	Yes	(2)	[ ]	No
6a. A violent argument between neighbors?	(1)	[ ]	Yes	(2)	[ ]	No
6b. More than once?	(1)	[ ]	Yes	(2)	[ ]	No
7a. A gang fight?	(1)	[ ]	Yes	(2)	[ ]	No
7b. More than once?	(1)	[ ]	Yes	(2)	[ ]	No
8a. A sexual assault or rape?	(1)	[ ]	Yes	(2)	[ ]	No
8b. More than once?	(1)	[ ]	Yes	(2)	[ ]	No
9a. A robbery or mugging?	(1)	[ ]	Yes	(2)	[ ]	No
9b. More than once?	(1)	[ ]	Yes	(2)	[ ]	No

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[11] Sampson RJ, Rauderbush SW, Earls F. 1997. Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. Science 277:918-924. Scale available: http://coglab.wjh.harvard.edu/soc/faculty/sampson/articles/1997_Science.pdf

INDIVIDUAL SOCIAL SUPPORT AND RESOURCES[12]

INTERVIEWER: *Next, I'll read you a list of statements each of which may or may not be true about you. You can respond "definitely true" if you are sure it is true about you and "probably true" if you think it is true, but are not absolutely certain. Similarly, you can respond "definitely false" if you are sure the statement is false and "probably false" if you think it is false but are not absolutely certain.*

1. I feel that there is no one I can share my most private worries and fears with.
2. When I need suggestions on how to deal with a personal problem, I know someone I can turn to. [rev score]
3. I don't often get invited to do things with others.
4. If I wanted to have lunch with someone, I could easily find someone to join me. [rev score]
5. If I were sick, I could easily find someone to help me with my daily chores. [rev score]
6. If I was stranded 10 miles from home, there is someone I could call who could come and get me. [rev score]
7. I have little control over the things that happen to me.
8. I often feel helpless in dealing with the problems of life.
9. What happens to me in the future mostly depends on me. [rev score]
10. I can do just about anything I really set your mind to do. [rev score]
11. In uncertain times, I usually expect the best [rev score]
12. I'm always optimistic about my future [rev score]
13. I hardly ever expect things to go my way
14. I rarely count on good things happening to me

RESPONSE OPTIONS:

1. Strongly Disagree 4. Strongly Disagree
2. Disagree 5. Don't know
3. Agree

[12] **Q1-6:** From the Interpersonal Support Evaluation List (ISEL):

Cohen S, Mermelstein R, Kamarck T, Hoberman H. 1985. Measuring the functional components of social support. In I. G. Sarason & B. R. Sarason (Eds.), In: *Social support: Theory, research, and application*. The Hague, Holland: Martinus Nijhoff.

Modification of ISEL items following rationale of: (a) retaining 2 items within each of the 3 domains of support (1,2=Appraisal; 3,4=Belonging; 5,6=Tangible), (b) brevity, (c) non-repetitiveness with social capital or cohesion scales, and (d) relevance to adults of all ages. This rationale matches the approach of study of social support and cardiovascular health among older adults in the Cardiovascular Health Study:

Martire LM, Schulz R, Mittelmark MB, Newsom JT. 1999. Stability and change in older adults' social contact and social support: The Cardiovascular Health Study. *Journals of Gerontology: Series B: Psychological Sciences and Social Sciences*, 54B(5), S302-S311.

Q7-10: Sense of control items (Q89, 92, 94, 95) from:

Lachman, M. E., & Weaver, S. L. (1998). The sense of control as a moderator of social class differences in health and well-being. *J Pers Soc Psychol, 74*(3), 763-773.

Pearlin LI, Schooler C. 1978. The structure of coping. *Journal of Health and Social Behavior, 19*, 2-21.

Q11-14: Optimism items (Q1, 5, 8, 10) from Life Orientation Test:

Scheier, M. F., Carver, C. S., & Bridges, M. W. (1994). Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A reevaluation of the Life Orientation Test. *Journal of Personality and Social Psychology, 67*, 1063-1078.

EVERYDAY UNFAIR TREATMENT[13]

INTERVIEWER: In your day-to-day life how often have any of the following things happened to you?

1. You are treated with less courtesy or respect than other people.
2. You receive poorer service than other people at restaurants or stores.
3. People act as if they think you are not smart.
4. People act as if they are afraid of you.
5. You are threatened or harassed.

Response Categories:

(1) Never
(2) Less than once a year
(3) A few times a year
(4) A few times a month
(5) At least once a week
(6) Almost everyday

Follow-up Question only of those answering "A few times a year" or more frequently to at least one question, asked only once for all experiences.

6. What do you think is the main reason for these experiences?

Response Options (CHECK MORE THAN ONE IF VOLUNTEERED).

1. Your Ancestry or National Origins
2. Your Gender
3. Your Race
4. Your Age
5. Your Religion
6. Your Height
7. Your Weight
8. Some other Aspect of Your Physical Appearance
9. Your Sexual Orientation
10. Your Education or Income Level
11. Other (SPECIFY) ____________________________

[13] Sternthal, M., Slopen, N., Williams, D.R. "Racial Disparities in Health: How Much Does Stress Really Matter?" Du Bois Review, 2011; 8(1): 95-113. Scale available: http://scholar.harvard.edu/davidrwilliams/pages/everyday-discrimination-scale-0

LIFE EVENTS[14]

INTERVIEWER*: Now I'll read you a list of events. Please indicate whether the event happened to you during the past year.*

1. Life-threatening illness or accidental injury?
2. Life-threatening illness or accidental injury to someone you are close to?
3. Fired from a job?
4. Did not have a job for 3 months or longer when you wanted to be working?
5. Anyone else in your household been unemployed and looking for work for longer than 3 months?
6. Moved to a worse residence or neighborhood?
7. Being robbed or your home burglarized?
8. Being mugged or assaulted?
9. Serious financial problems or difficulties?
10. Spouse/partner engaged in infidelity?
11. Divorced or separated from a spouse/partner?
12. Legal trouble or trouble with police?
13. Anything else bad happened to you that upset you a lot?
14. Anything else bad happened to someone you are close to that upset you a lot?

Response Options:

1. Yes
2. No

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[14] Adapted from the National Comorbidity Survey Baseline Interview Schedule.
Scale available: http://www.hcp.med.harvard.edu/ncs/ftpdir/Baseline%20NCS.pdf

Adapted from the National Comorbidity Survey Baseline Interview Schedule:
- Q1-2 separated from single item
- Q8 added to distinguish physical violence vs property-related crimes in Q7
- Q11 added
- Q12 added "or trouble with police" based on FG findings

Kessler RC, Wittchen H-U, Abelson JM, McGinagle KA, Schwartz N, Kendler KS, Knauper B, Zhao S. 1998. Methodological studies of the Composite International Diagnostic Interview (CIDI) in the US National Comorbidity Survey. Int J Methods Psychiatric Res 7(1):33-55.

HURRICANE SANDY QUESTIONS[15] (Winter wave only)

Interviewer: To finish up, I'll read you some questions about Hurricane Sandy.

1) As a result of Hurricane Sandy, were you or a loved one injured? Yes or No?
1= Yes 2= No

2) As a result of Hurricane Sandy, did you or a loved one experience a life-threatening situation? Yes or No?
1= Yes 2= No

3) As a result of Hurricane Sandy, were you evacuated or displaced from your home? Yes or No?
1= Yes 2= No

[If Yes to Q3]
4) For how long were you displaced?
1= Less than 24 hours
2= 1-2 days
3= 3-7 days
4= More than a week
5= More than a month
6= Still displaced

5) About how many people in your neighborhood were evacuated or displaced?
1= none
2= a few
3= about half
4= most
5= all

6) Did you have evacuees stay in your home?
1= Yes
2= No

7) Taking everything into account, how stressful would you say your experiences with Hurricane Sandy and the aftermath have been, on a 0-to-10 scale, where 0 means not at all stressful and 10 means the most stressful thing you can imagine?

8) People lost many things because of Hurricane Sandy - loved ones, property, a sense of community, and a way of life. On a 0-to-10 scale where 0 means no loss and 10 means the greatest loss you can imagine, what number describes how much you lost because of the storm?

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[15] Adapted from Hurricane Katrina Community Advisory Group, Harvard Medical School, Department of Health Care Policy. Baseline survey January-April 2006.
Scale available: http://www.hurricanekatrina.med.harvard.edu/pdf/baseline_overview_1-06.pdf

Kessler RC, Galea S, Gruber MJ, Sampson NA, Ursano RJ, Wessely S. 2008. Trends in mental illness and suicidality after Hurricane Sandy. Mol Psychiatry 13(4):374-384.

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