Susceptibility to Multiple Air Pollutants in Cardiovascular Disease

Jane E. Clougherty[1], Laura D. Kubzansky[2], Colleen Reid[3], Ellen Kinnee[4], Leslie McClure[1], David Q. Rich[5], Fernando Holguin[6]

[1] Drexel University Dornsife School of Public Health, Philadelphia PA, [2]Harvard T.H. Chan School of Public Health, Boston MA, [3]University of Colorado at Boulder, [4] University of Pittsburgh Graduate School of Public Health; [5]University of Rochester School of Medicine and Dentistry, [6] University of Colorado at Denver School of Medicine

Introduction and Background

Cardiovascular disease (CVD) is the leading cause of death in the U.S., and substantial research links ambient air pollution to CVD risk (Brook et al 2009; Kaufman et al 2016). Some research identifies greater exposures and impacts in lower socioeconomic position (SEP) communities (Clark et al. 2014; Krewski et al, 2003). Elucidating the factors which explain SEP-related susceptibility to pollution has been identified as a research priority (US EPA 2008).

Some evidence suggests that SEP-related susceptibility may be mediated, in part, via chronic stressor exposures (e.g., violence, job insecurity) (Clougherty et al 2014; Shankardass et al 2009). These combined exposures may be particularly relevant to CVD risk (Hicken et al 2014), as both pollution and stressors are linked to inflammation, metabolic function, oxidative stress, hypertension, and atherosclerosis (Everson-Rose 2014; Kubzansky et al 2007). Because pollution and stressors may be spatially correlated (Jones et al., 2014), disentangling their effects – and quantifying any interplay -- is especially challenging. Doing so, however, will help to better identify and characterize susceptible populations, more effectively target interventions, and strengthen cost-benefit and accountability analyses.

We hypothesize that:

(1) *Chronic exposures to multiple pollutants and SEP/ stressor exposures together shape community CVD event rates.*

(2) *Associations between spatio-temporal variation in multiple pollutants and CVD risk will be greater in communities of lower SEP and/ or higher stressor exposures.*

Specific Aims

We will quantify relationships among chronic stressors and multiple pollutants in NYC, and test whether pollutant-CVD relationships vary by SEP/ stressor exposures.

Aim 1: In ecologic cross-sectional analyses, test whether exposures to annual-average chronic stressor rates and annual-average pollutant exposures, separately and together, predict community age-adjusted CVD event rates.

Aim 2: Quantify associations between $PM_{2.5}$, NO_2, and O_3 exposures, separately and together, and CVD events, using individual-level ED data in case-crossover models with spatio-temporal exposure estimates for residential location and visit date, testing effects across 0 - 6 lag days.

Aim 3: Examine whether SEP/ stressors exacerbate effects of pollutant exposures on CVD, using 'validated' indicators of community SEP/ stressor exposures in case-crossover models.

Methods: Datasets

(1) **Hospital CVD data:** Data on all in- and outpatient unscheduled cardiovascular events (ICD-9 codes 390-459) at NYC hospitals 2005-2011 (n = 843,958) is provided by NY State Dept. of Health Statewide Planning and Research Cooperative System (SPARCS). We use "emergent" and "urgent" admissions, indicating acute events.

(2) **Citywide air pollution data:** NYC Community Air Survey (NYCCAS), one of the largest studies of intra-urban variation in multiple pollutants, was established by the NYC Dept. of Health & Mental Hygiene (DOHMH) to inform policy and air quality initiatives. Spatial saturation monitoring was performed year-round at 155 sites across NYC for two years (Matte et al. 2013). Land Use Regression was used to model spatial variation in fine particles ($PM_{2.5}$), elemental constituents, nitrogen dioxide (NO_2), and summertime ozone (O_3) (Clougherty et al. 2013).

(3) **Daily EPA data:** We wiil use daily averages from 7 NYC Air Quality System (AQS) stations for 2005-2011. We examined data missingness, imputed missing values, and averaged daily values from all sites into one mean trend (Sheffield et al., 2015). We combine this 'citywide' trend with NYCCAS surfaces to create day- and home-specific 'spatio-temporal' estimates (Ross et al. 2013; Shmool et al. 2015).

Datasets Cont'd

4) GIS-based area-level susceptibility indicators: We will examine effects of community-level susceptibility using 3 different types of SEP/ stressor indicators:

4a) Socioeconomic deprivation index (SDI): To capture relative material deprivation, we used spatially-stratified principal components analysis (PCA) (Messer et al, 2006) on 20 indicators [education, employment, occupation, housing, poverty, racial/ethnic composition) from American Communities Survey (ACS) 2005-09, at census tract. We ran PCAs city-wide, then by borough, then re-ran the city-wide PCA retaining all variables loading > |0.4| in 2 or more boroughs. The final SDI had 7 variables, explaining 56% of variance. (Figure 1).

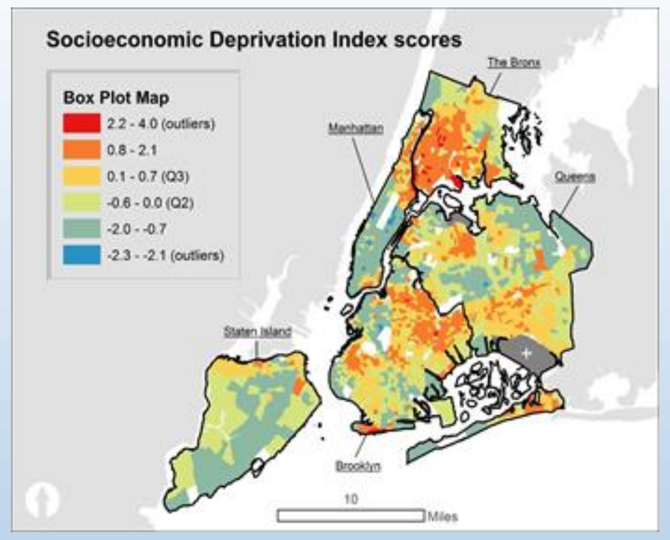


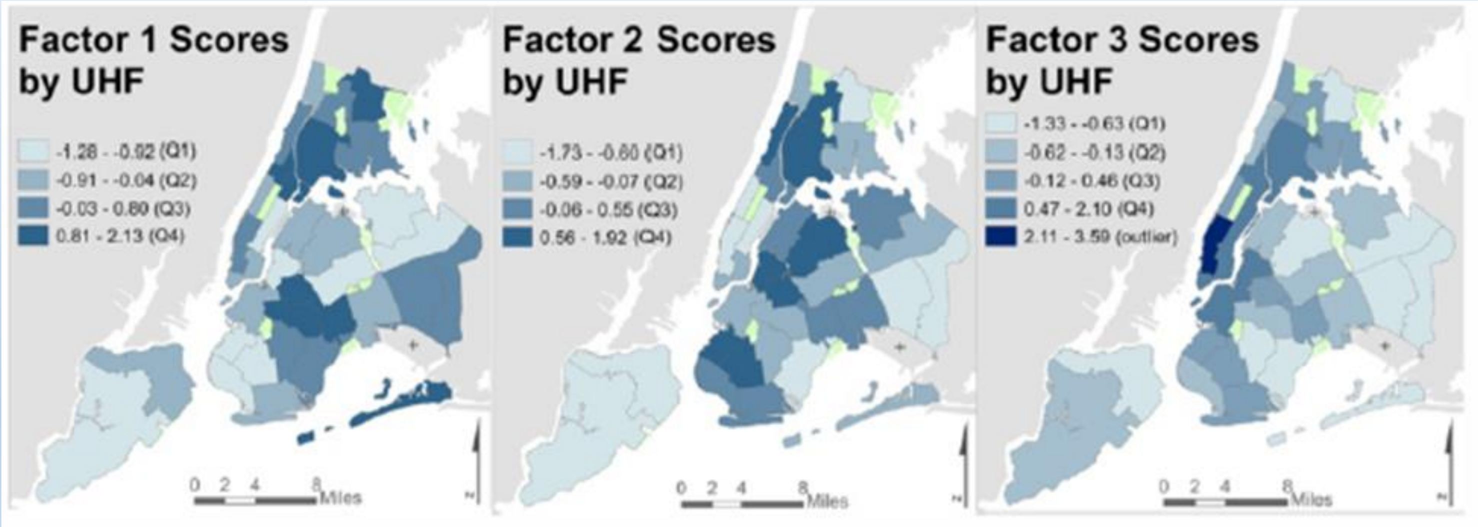
Figure 1: Socioeconomic Deprivation Index

4b) Spatially-correlated stressor factors: We aggregated, re-formulated, and examined 27 stressor indicators, across 6 categories, from administrative data sources (Table 1). We required citywide coverage, conceptual comparability with validated measures in our citywide stress survey [e.g., Perceived Neighborhood Disorder (Ross & Mirowsky 2001)], and excluded indicators with substantial under-reporting or reporting bias (e.g., felony rape). We used unconstrained factor analysis with and without spatial autocorrelation adjustment (Shmool et al. 2014) (Figure 2).

Table 1: Community stressor indicators.

Stressor Construct	Administrative Indicator	NYC Agency	Aggregate Unit	Date
Crime & Violence	Felony Larceny Crimes	Police Department (NYPD)	PP	FY2009
	Felony 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 2: Three spatial factors: Factor 1 was characterized by violence & physical disorder; Factor 2 by crowding & low resource access; Factor 3 by noise & air pollution complaints.



4c: Key stressors: Assault rate, Percent of households < 200% of federal poverty level: In 'validating' stressor indicators using focus group and survey data, these 2 indicators best predicted perceived neighborhood disorder and mental health (perceived stress, anxiety, depression), thus we examine these individually.

Analysis Plan

Aim 1: Because social stressor data is aggregated to community annual averages, we will conduct ecologic cross-sectional analyses to compare associations for annual-mean pollution and stressors against age-adjusted annual-mean community CVD rates, for the composite of ICD-9 codes 390-459, and key diagnoses therein (i.e., myocardial ischemia/ infarction, arrhythmias, heart failure, cardiac arrest). We test pollutant interactions with median-dichotomized and categorical stressor modifiers, adjust for autocorrelation using Simultaneous Autoregression (SAR) with 1st-order weights, and Moran's *I* to test autocorrelation in OLS residuals (Anselin 2005).

To depict the method, we examined annual-average NO_2 against asthma ED visits among children aged 0-14 (2008-10), modified by the 3 stressor factors in Figure 2. As shown in Figure 3, we found a significant main effect on asthma only for Factor 1 ('violent crime & physical disorder'), and significant modification of NO_2 effects only by Factor 2 ('crowding & poor resource access') (Shmool et al. 2014).

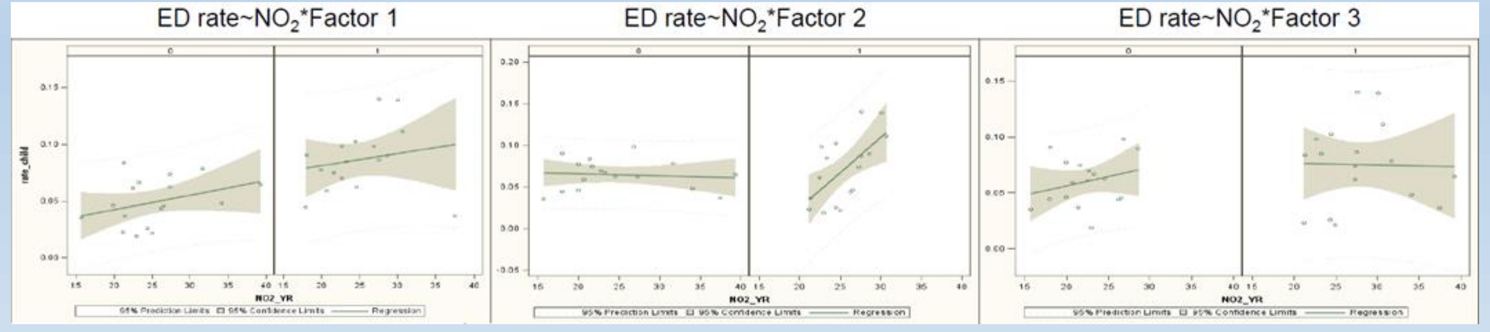


Figure 3: Annual average UHF-area NO2 and asthma ED visits, by 3 median-dichotomized stressor factors.

Aim 2: We will examine daily $PM_{2.5}$, NO_2, and O_3 vs. 843,958 CVD events at in 2005-2011 using conditional logistic regression in case-crossover. Using bi-directional referent sampling to control for time-invariant confounders (e.g., sex, race), we adjust for temperature and co-pollutants, and estimate risk per 10-unit pollutant increase, on lag days 0-6, as: (mean NYCCAS concentration within 300 m of home / citywide NYCCAS mean) x daily AQS mean (Ross et al 2013; Shmool et al 2016).

Aim 3: We will test modification in associations between spatio-temporal exposures and risk of CVD event, using the models described above, in interaction with categorical stressor modifiers and Bonferroni adjustment for multiple comparisons. Figure 9 shows that, on each lag day 0-6, we observe stronger effects of O_3 on asthma in communities with more violent crime (Q1-Q3).

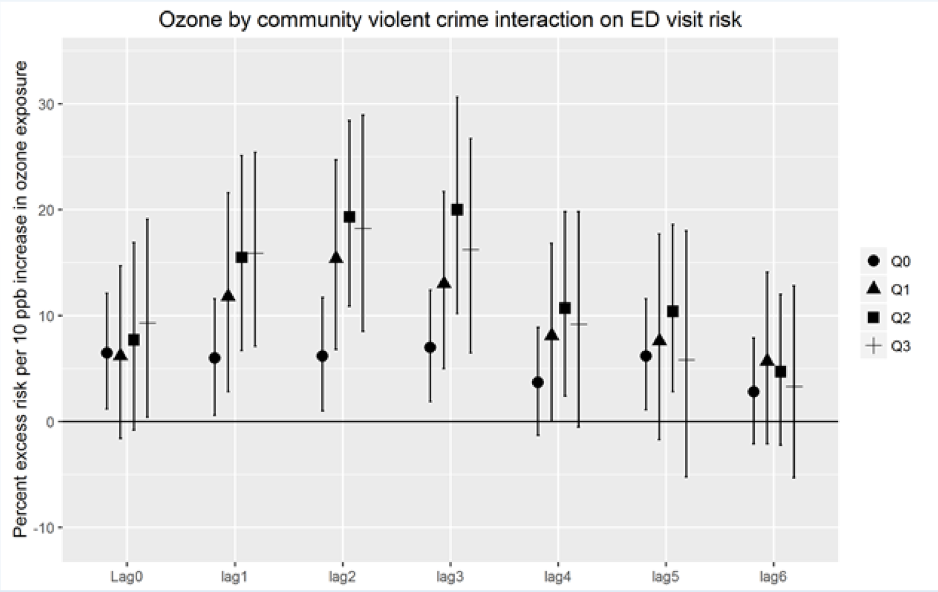


Figure 4: Excess risk of asthma ED visit per 10 ppb O_3, by quartile of violence (low crime ref = Q0).

Anticipated Results

We expect to observe stronger associations between spatio-temporal pollution exposures and CVD events in lower-SEP communities. Our process for disentangling the many stressors which comprise SEP - and examining effect modification by these stressors separately - may help to more clearly identify those aspects of lower SEP which most influence pollution response, and shed insight on possible pathways for susceptibility.

References

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