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Short communication

Environmental inequality: Air pollution exposures in California's South Coast Air Basin

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Abstract

Environmental inequality is quantified here using linear regression, based on results from a recent mobility-based exposure model for 25,064 individuals in California's South Coast Air Basin [Marshall et al., 2006. Inhalation intake of ambient air pollution in California's South Coast Air Basin. Atmospheric Environment 40, 4381–4392]. For the four primary pollutants studied (benzene, butadiene, chromium particles, and diesel particles), mean exposures are higher than average for people who are nonwhite, are from lower-income households, and live in areas with high population density. For ozone (a secondary pollutant), the reverse holds. Holding constant attributes such as population density and daily travel distance, mean exposure differences between whites and nonwhites are 16–40% among the five pollutants. These findings offer a baseline to compare against future conditions or to evaluate the impact of proposed policies.

Keywords: Environmental justice; Geographic information systems; Mobility-based spatiotemporal exposure model; Particulate matter; $PM_{2.5}$; Vehicle emissions

1. Introduction

Understanding exposure variations among subpopulations is important for risk management, epidemiology, and environmental justice. Environmental health policy seeks not only to reduce population-average risk, but also to ensure that specific subpopulations are not unduly burdened relative to the overall population (Anand, 2002). Previous research has documented higher outdoor air pollution in regions with a greater portion of nonwhite and low-income groups in California's South Coast Air Basin (SoCAB) (Morello-Frosch et al., 2001, 2002) and elsewhere (Bell et al., 2005; Brown, 1995; Brulle and Pellow, 2006). Low socioeconomic-position groups tend to have high vulnerability to air pollution, i.e., a given exposure level may cause greater-than-average health reduction for these groups (O'Neill et al., 2003; Samet and White, 2004).

This short communication explores environmental equality for air pollution exposure in California's SoCAB. Marshall et al. (2006), presenting a new mobility-based exposure model, documented air pollution inequalities among ethnic and income subpopulations; however, they did not report whether these inequalities persist after accounting for differences in attributes such as education, daily travel distance, and neighborhood population

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density. For example, because low population-density areas generally have low primary pollutant concentrations and also tend to have high income and be white, the question arises as to whether white/nonwhite exposure differences are attributable solely to differences in population density. I address this question here using linear regression. Findings indicate that exposure inequalities by ethnic and income group persist even after accounting for population density, daily travel distance, and other attributes.

2. Methods

Air pollution exposure estimates are derived from a spatiotemporal exposure model of 25,064 individuals in the SoCAB. The model was described previously in this journal (Marshall et al., 2006). Five pollutants are studied: benzene, 1,3-butadiene, ozone, fine particulate matter emitted from diesel engines ($DPM_{2.5}$), and hexavalent chromium in the form of fine particulate matter ($CrPM_{2.5}$). Results reflect (indoor and outdoor) exposure to pollution of outdoor origin only.

Because exposure estimates employed here are log-normally distributed, the dependent variable in the regressions (SAS v9.1, PROC REG) is the logarithm of exposure concentration. Geometric mean exposure concentrations are used to compare central tendencies among subpopulations. Independent variables, listed in Table 1, are parameters hypothesized in advance as potentially important for exposures (see Fig. 1).

3. Results

3.1. Descriptive statistics

For traffic-related pollutants, exposures are positively correlated among primary pollutants (Pearson correlation coefficients: 0.94 for benzene-butadiene; 0.83 for benzene-$DPM_{2.5}$; 0.77 for butadiene-$DPM_{2.5}$), and negatively correlated with ozone exposures (Pearson: −0.47 for ozone-benzene; −0.46 for ozone-butadiene; −0.39 for ozone-$DPM_{2.5}$). As a result, exposure trends frequently differ between primary pollutants and ozone.

Geometric mean exposures (Fig. 1) and arithmetic mean exposures (not shown) are ~50% higher (for ozone: ~35% lower) for lower-income (<\$50,000 annual household income) nonwhites than for higher-income (>\$50,000) whites. Expo-

Table 1
Coefficients (standard errors) of linear regressions for exposure concentrations, by pollutant[a,b]

Pollutant	Variable	Whites	Nonwhites
$DPM_{2.5}$	(Intercept)	0.231 (0.008)	0.350 (0.008)
	Lower-income	–	–
	Population density	0.286 (0.014)	0.120 (0.010)
	Travel distance	0.127 (0.007)	0.126 (0.010)
	Model R^2	0.055	0.032
$CrPM_{2.5}$	(Intercept)	−4.38 (0.01)	−4.18 (0.01)
	Lower-income	–	0.0184 (0.0110)†
	Population density	0.340 (0.018)	0.167 (0.012)
	Travel distance	0.0843 (0.0099)	0.0431 (0.0128)‡
	Model R^2	0.039	0.027
Benzene	(Intercept)	0.472 (0.007)	0.570 (0.006)
	Lower-income	–	–
	Population density	0.263 (0.010)	0.151 (0.007)
	Travel distance	0.0724 (0.0056)	0.0764 (0.0076)
	Model R^2	0.074	0.053
Butadiene	(Intercept)	−0.757 (0.012)	−0.571 (0.009)
	Lower-income	−0.0350 (0.0106)	–
	Population density	0.594 (0.018)	0.329 (0.012)
	Travel distance	0.105 (0.010)	0.0965 (0.0121)
	Model R^2	0.11	0.085
Ozone	(Intercept)	0.916 (0.009)	0.787 (0.010)
	Lower-income	−0.0270 (0.0084)‡	−0.0265 (0.0092)‡
	Population density	−0.193 (0.014)	−0.0902 (0.0104)
	Travel distance	0.0640 (0.0075)	0.0917 (0.0104)
	Model R^2	0.038	0.035

[a]The dependent variable is the base-10 logarithm of exposure concentration ($\mu g\,m^{-3}$). Independent (explanatory) variables are as follows: two dummy variables (values: 0 or 1) for age category (under 7 years; over 65 years), two dummy variables for education level (high-school graduate; college graduate), two direct survey responses (male/female; household annual income above/below \$50,000), total straight-line ("crow-flight") distance traveled (calculated by the exposure model), and population density in the Census tract of the respondent's residence. For coefficients above, units are (1000 people km^{-2}) for population density and (100 $km\,d^{-1}$) for travel distance.

[b]All coefficients shown are significant at 0.0001, except as noted using the following significance scale: † = 0.10, ‡ = 0.005. Omitted coefficients ("–") are not significant at the 0.10 level. Model R^2 values (range: 3–11%) are statistically significant (<0.0001) even though they are low by conventional standards. The limited number of possible combinations for many independent variables (ethnicity, income, etc.) may reduce the maximum possible R^2 to below 1 (Weisberg, 2005). Large R^2 values are less important for the aim here, i.e., correcting for covariates, than for predictive models (McNamee, 2003). If exposures were *not* dependent on the predictive variables, the expected R^2 would be ~0.0004% (the number of data points divided by number of predictive variables (Weisberg, 2005)), or about two orders of magnitude lower than the R^2 values above, which further emphasizes that the model R^2 values above are statistically significant.

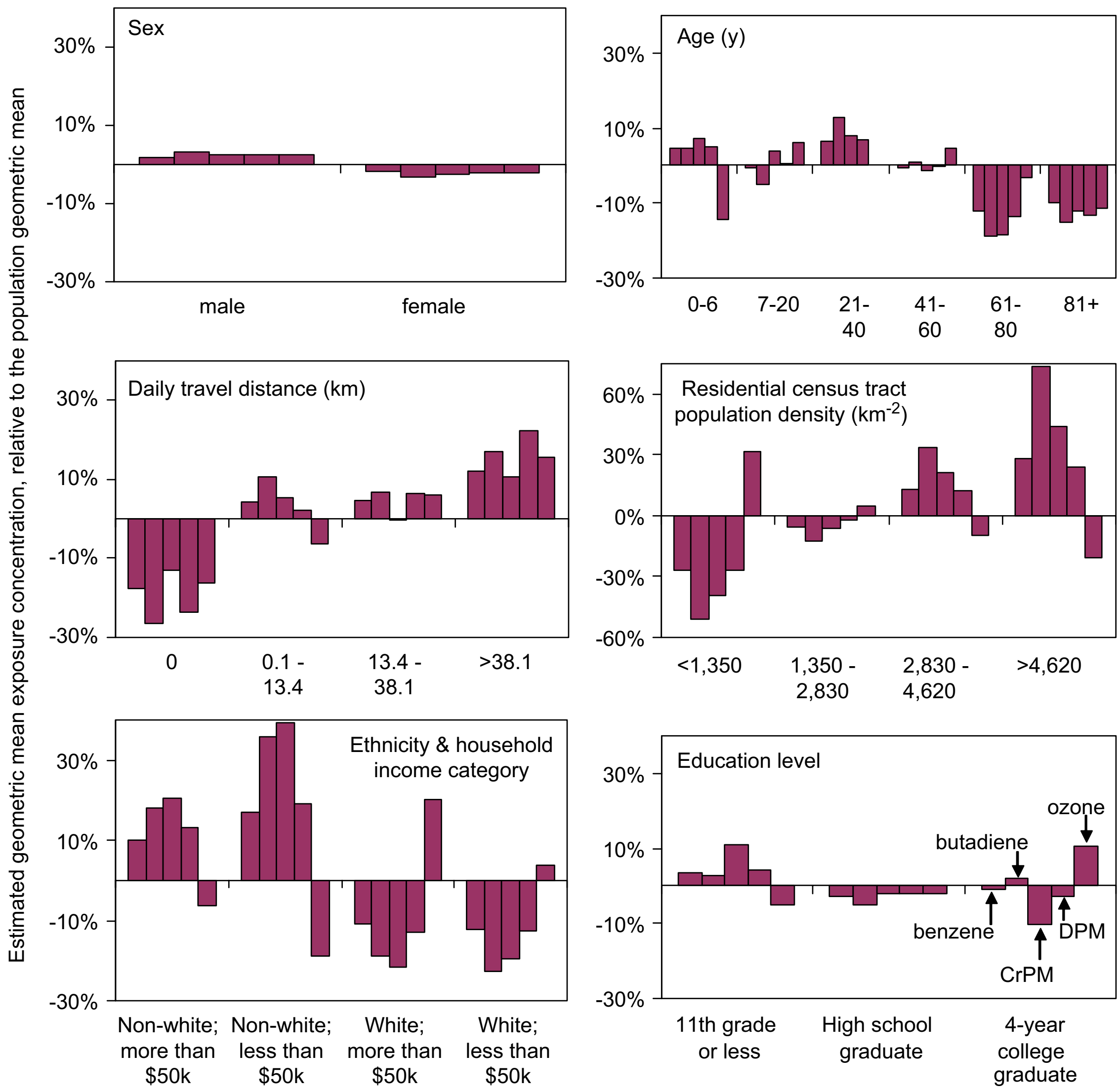

Fig. 1. Estimated geometric mean exposure concentration for each subpopulation relative to the overall population geometric mean. Values for the five pollutants are presented in the same order in each plot (left to right: benzene, butadiene, chromium $PM_{2.5}$ (CrPM), diesel $PM_{2.5}$ (DPM), ozone). Note that the ordinate scale for population density (middle right plot) differs from that of the other plots.

sure differences are larger between whites and nonwhites than between income categories. This finding is consistent with extant studies in the SoCAB (Morello-Frosch et al., 2002) and elsewhere (Ringquist, 2005).

High-exposure subpopulations (people with exposures above the 75th, 90th, and 95th percentiles) for primary pollutants are more likely than average to be low-income, to be nonwhite, and to reside in high-density areas. In contrast, average ozone exposures are lower for nonwhites, lower-household-income individuals, young children (0–6 years old), and individuals residing in high-density areas. Mean densities (km^{-2}) for the top 25% and 5% of the exposure distributions, respectively, are 2900 and 2110 for ozone, compared to 4590 and 5230 averaged among primary pollutants. The overall mean density is 3580 km^{-2}.

3.2. Linear regression model

Table 1 presents ethnicity-stratified linear regression results for exposure concentration. For example, for nonwhites, increasing population density by 1000 km^{-2} yields a 32% increase in $DPM_{2.5}$ exposure concentration (i.e., a 0.12 increase in the logarithm of exposure) and a 19% decrease in ozone exposure. As expected, the regression models have low R^2 values (range: 3–11%): there is significant scatter in the exposure estimates, only some of which is explained by the independent variables employed. Nevertheless, all models are significantly better than the null (p-values <0.0001). Equations in Table 1 reveal underlying trends and are not intended for exposure prediction. In many cases, income category is not a statistically significant predictor of exposure, corroborating from Fig. 1 that exposures vary more by ethnicity than by income category.

Results indicate higher primary-pollutant exposures (lower ozone exposures) for nonwhites than for whites, even after accounting for covariates such as population density. White/nonwhite differences in exposure concentrations for a male with median demographic characteristics (age 7–64 years; high school but not college education; neighborhood population density is 2830 km^{-2}; personal daily travel distance is 13 km; household income is >\$50,000) are 16–21% for benzene, $DPM_{2.5}$, and ozone; 29% for butadiene; and 40% for $CrPM_{2.5}$. Analogous white/nonwhite differences for household income <\$50,000 are similar for benzene, $DPM_{2.5}$, and ozone, and higher for butadiene (39%) and $CrPM_{2.5}$ (47%). The magnitude of these differences is striking.

To confirm Table 1 results, separate regressions were generated for five pseudo-random data subsets, wherein survey responses were limited to the following: (1) diary day is Sunday; (2) diary day is Tuesday; (3) diary day is Friday; (4) household size is four persons; and (5) employer business type has no answer recorded. The rationale for this analysis is that if linear regression models for the five subsets are consistent with Table 1 results—which turns out to be true—then that increases confidence in the robustness of the findings.

Regression coefficients for population density are greater for whites than nonwhites, indicating that exposure differences between more- and less-dense areas are larger for whites than for nonwhites. This finding suggests the primary-pollutant hypothesis that in dense regions of the SoCAB, ambient concentrations are generally high and all individuals receive comparatively high exposures, whereas sparser regions contain greater concentration heterogeneity, thereby allowing greater exposure variability among subpopulations. More work is needed to investigate this hypothesis. An important implication is that environmental equality concerns hold throughout the urban area, not only in the high-density urban core.

Table 2
Example distributive justice frameworks in the context of air pollution exposures[a]

Equality of outcome: Exposures should be equal for all individuals. Central tendencies (e.g., mean values) for important subpopulations should be equal.

Equality of health impact: Environmental health impacts (risks; disease rates) should be equal for all individuals. Central tendencies for important subpopulations should be equal.

Welfare-maximizing: The distribution of exposures should be such that the population burden-of-disease is minimized.

Equality of opportunity: Individuals and subpopulations should have equal opportunity to reduce or avoid exposures.

Fairness: Inequality should yield the greatest benefit for the worst off. Here, this would imply lower exposures for more susceptible individuals. Susceptibility to air pollution may derive from attributes such as age, socioeconomic position, pre-existing disease, and genetics.

History: If individuals and groups with lower exposures obtained that position fairly, then the distribution is just. If other individuals have higher exposures, this fact is largely irrelevant.

Minimum standard: The worst-off should not fall below a certain standard. The standard can be relative (e.g., the difference between best- and worst-off) or absolute (e.g., a health-based concentration standard).

Cost–benefit matching: Environmental health impacts (costs) of a technology should be proportional to the benefits derived from that technology (e.g., for motor vehicles: personal mobility and access to shipped goods; for power plants: use of electricity-consuming products and services).

[a]This table focuses on distributable justice (the distribution of pollution exposures among individuals) rather than retributive justice (correcting for historic wrongdoings) or procedural justice (the decision-making process itself).

4. Discussion

The results presented above document environmental *inequality*, not environmental *justice*. While those two phrases are often used interchangeably, they are distinct (Waller et al., 1999): situations can be equal but unjust, or just but unequal. For example, one might believe that a person who drives more should have higher exposure to vehicle emissions, or that a person with high susceptibility should have low exposures. Such value judgments are not explicitly incorporated into equality indices. Table 2 provides example justice frameworks as applied to air pollution exposures. This table is illustrative, not exhaustive; it highlights that justice is normative and is distinct from equality.

The goal for environmental policy, of course, is to identify and eliminate environmental *in*justice. An important step towards that goal is generating useful metrics to aid in evaluating policy options, comparing among pollutants and locations, and tracking progress over time. Environmental managers will be better able to improve environmental justice conditions when they can measure their own progress and when stakeholders can hold them accountable for firm, systematic improvements. This paper aims to contribute to that goal.

5. Conclusion

Regression results for a new, mobility-based exposure model indicate environmental inequality for air pollution exposures in the South Coast, even after accounting for covariates such as population density. At median values for the independent variables, white/nonwhite exposure differences are 16–40%. Compared to whites, nonwhites have higher exposures for primary pollutants (benzene, butadiene, chromium particles, and diesel particles) and lower exposures for ozone.

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