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Disparities in Exposure to Automobile and Truck Traffic and Vehicle Emissions Near the Los Angeles–Long Beach Port Complex

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Objectives. We assessed how traffic and mobile-source air pollution impacts are distributed across racial/ethnic and socioeconomically diverse groups in port-adjacent communities in southern Los Angeles County, which may experience divergent levels of exposure to port-related heavy-duty diesel truck traffic because of existing residential and land use patterns.

Methods. We used spatial regression techniques to assess the association of neighborhood racial/ethnic and socioeconomic composition with residential parcel-level traffic and vehicle-related fine particulate matter exposure after accounting for built environment and land use factors.

Results. After controlling for factors associated with traffic generation, we found that a higher percentage of nearby Black and Asian/Pacific Islander residents was associated with higher exposure, a higher percentage of Hispanic residents was associated with higher traffic exposure but lower vehicle particulate matter exposure, and areas with lower socioeconomic status experienced lower exposure.

Conclusions. Disparities in traffic and vehicle particulate matter exposure are nuanced depending on the exposure metric used, the distribution of the traffic and emissions, and pollutant dispersal patterns. Future comparative research is needed to assess potential disparities in other transportation and goods movement corridors. (*Am J Public Health.* Published online ahead of print May 16, 2013: e1–e9. doi:10.2105/AJPH.2012.301120)

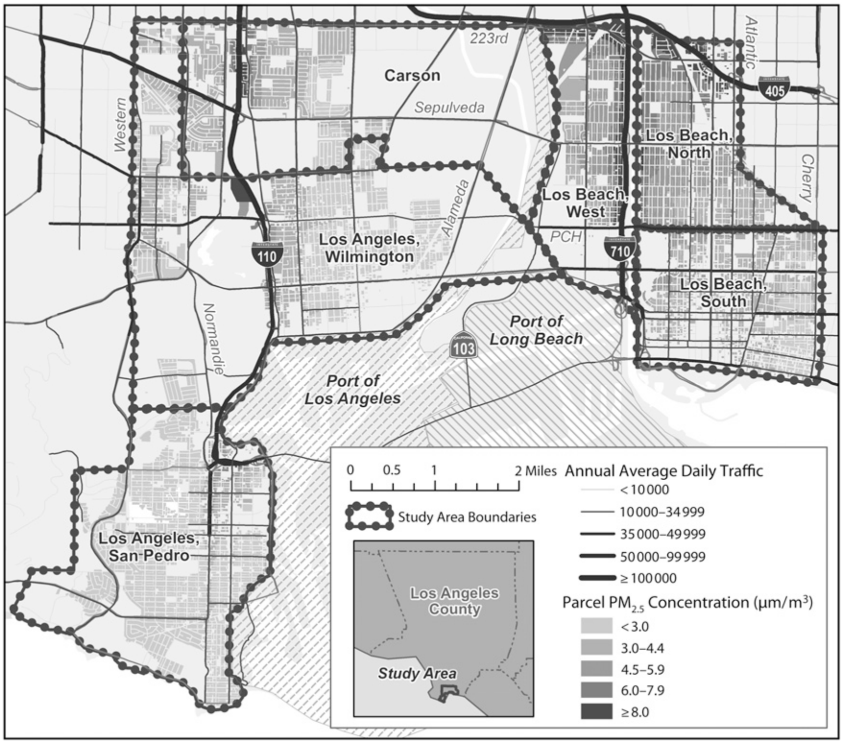
Residential proximity to heavy traffic has been associated with adverse health effects, including asthma, reduced lung function, cardiac and pulmonary mortality, and adverse birth outcomes.[1–3] Previous research suggests that non-White and lower income individuals may be exposed to higher levels of traffic-related air pollution[4–8] and that disparities vary with social gradients associated with higher susceptibility to pollution.[9,10] Environmental justice concerns are heightened in goods movement corridors in which substantial volumes of heavy-duty diesel trucks (HDDTs) transport shipping containers on arterials near residences and sensitive land uses through lower socioeconomic status communities.[11,12]

Significant questions remain, however, regarding the existence and magnitude of race- and income-based disparities in traffic and air pollution exposure.[13–16] Some studies have found little association between air pollution exposure and socioeconomic status after controlling for confounding factors[17]; others found greater air pollution and traffic exposure for higher socioeconomic groups.[18,19] Such discrepancies could arise because of methodological differences and challenges in assessing inequities at various scales.[11,20–22] Scale could be an important consideration in assessing traffic impacts because vehicle-related pollutants are highly localized, with pollutant concentrations decaying to background levels within 200 to 300 meters during the day,[23–26] and because ambient air quality monitoring data are likely insufficient to characterize near-roadway pollutant gradients.

Our study provides an important environmental justice case study by assessing how traffic and mobile-source air pollution impacts are distributed across groups in port-adjacent communities in southern Los Angeles County, which contain substantial racial/ethnic and socioeconomic diversity and may experience divergent levels of exposure to port-related HDDT traffic because of existing residential and land use patterns.[12,27,28] We have contributed to the environmental justice literature by examining exposures at the parcel property assessment level to determine impacts at a finer spatial resolution,[29] by using spatial regression techniques to account for spatial dependence of data when assessing disparities,[30–33] and by using 3 parcel-level metrics of exposure that could have different spatial distributions and population impacts: total nearby vehicle miles traveled (VMT), nearby truck VMT, and the modeled concentrations of emissions from vehicles on neighborhood roadways. We hypothesized that the first 2 traffic exposure measures would provide a distance-based assessment of near-roadway exposure to traffic-related noise and air pollution and that the third would account for the air pollution "plume" after accounting for the geographic and temporal variation in traffic, wind, and other meteorological patterns.

METHODS

The study area covers approximately 35 square miles immediately adjacent to the ports of Los Angeles and Long Beach in southern Los Angeles County, California, and is transected by a roadway network that carries substantial passenger and diesel truck traffic (Figure 1). The I-110 freeway on the western edge of the port complex carries substantial commuter traffic and about 12% HDDTs; the I-710 freeway on the eastern edge carries about 25% container truck traffic.[28] Substantial port-related HDDT traffic travels through the study communities en route to and from these freeways, truck facilities, and transfer yards.[12]



Note. PM = particulate matter.

FIGURE 1—Study area and distribution of vehicle particulate matter for residential parcels: Southern Los Angeles County, CA, 2005.

Scale of Analysis

Our study is the first environmental justice study to our knowledge to assess disparities using parcel-level data. We obtained the geographic boundaries and characteristics (use type and the year the structure was built) from the Los Angeles County tax assessor.[34] Previous studies have analyzed variation in exposure to urban air pollutants that disperse at the neighborhood level and regional level using zip code and census tracts, block groups (BGs), or blocks.[32,33,35,36]

Parcel-level data could more precisely assess the population impacts of near-roadway pollutant concentrations that decay to background levels within 200 to 300 meters during the day.[23–26] When possible, the scale used for analysis should match the geographic patterns of the generation and diffusion of the hazard.[17,21,22,31]

Dependent Variables

We developed 3 measures of exposure to assess the robustness of findings across multiple metrics. We developed our first 2 exposure measures, total nearby VMT and total nearby truck VMT, on the basis of a consolidated traffic database previously described.[37] In our analysis, we generally define "nearby" to be within 250 meters, a distance threshold that corresponds closely to the distance from roadways at which vehicle-related air pollutants drop to near-background concentration levels.[26] This consolidated traffic database incorporates passenger vehicle and HDDT counts for freeways and major arterials and was derived from state and city departments of transportation, port authorities, transportation studies, and truck route designations. Accounting for HDDTs is important in the study area because the California Air Resources Board has declared diesel exhaust particulates emitted from HDDTs a toxic air contaminant,[38] HDDTs have substantially higher particulate emission rates than do gasoline vehicles,[39] about 70% of cancer risk from air toxins in Southern California is attributed to diesel particulate emissions,[40] and about 84% of containers leaving the port complex are transported via HDDT.[28]

Our third exposure measure represents the previously described[37] parcel-level–modeled concentration of emissions from vehicles on neighborhood roadways, which we derived from a modified CALINE4 line dispersion model of vehicle-related pollution including particulate matter (PM) less than 2.5 µm ($PM_{2.5}$) on the basis of traffic volumes, vehicle class, and meteorological conditions. Line dispersion models use Gaussian plume equations to estimate pollution concentrations with increasing distance from an emission source, such as a roadway, by accounting for factors such as traffic volume, emission factors by vehicle type, meteorological conditions, atmospheric mixing heights, and topography.[41]

The California Department of Transportation and the US Federal Highways Agency developed the CALINE4 model.[42] The model employs a mixing zone concept to characterize pollutant dispersion over the roadway. We ran the CALINE4 model simulations to estimate parcel-level $PM_{2.5}$ concentrations from local traffic emission within 3 kilometers of a residence in a summer (August) and a winter

(January) month in 2005 using vehicle emission factors from the California Air Resources Board's EMFAC2007 and 2005 meteorological data from the National Weather Service at the Long Beach Airport, which is located at the eastern edge of the study region. Figure 1 shows the distribution of the modeled parcel-level concentrations of $PM_{2.5}$ from vehicle traffic emissions in the study area. As previously reported, our model suggests that local traffic near the port complex contributes almost a fourth of total fine PM in the study area.[37]

Independent Variables

We conceptualized variables for the nearby transportation infrastructure, land use, employment, and parcel-level characteristics to exert a direct influence on the level of nearby traffic- and vehicle-related pollution. That is, they are likely directly related to the presence of nearby traffic and the volume of pollution generation.[41,43] We expected the total mileage of nearby truck routes and major nontruck roadways, which we derived from a previously described[37] consolidated traffic database, to have a direct influence on the volume of nearby traffic and level of associated pollution.

We obtained 2005 land use data and 2008 InfoUSA business location and employment data from the Southern California Association of Governments to account for proximity to potential traffic-generating land uses such as commercial districts, job centers, and mixed-use areas (≥ 25% nearby residential and ≥ 25% commercial use).[44] We used a previously described[45] firm classification scheme to identify firms that were neighborhood-serving businesses on the basis of a firm's standard industrial classification code to identify nearby land uses that could be associated with more localized, shorter vehicle or walking trips.

A parcel's residential use type may be related to nearby traffic levels because multifamily parcels may generate more vehicle trips. Also, older housing structures tend to have higher levels of nearby traffic, which raises concerns because these building types tend to have higher rates of indoor exposure to outdoor pollutants, including intrusion of motor vehicle exhaust.[6,46]

We used the city or municipality a parcel was located in as a control variable because services such as public amenities and schools could vary substantially across jurisdictions and could impact residential location choices (Figure 1).[47] Although some previous studies have raised concerns regarding the inclusion of regional dummy variables in spatial regression models,[32] our likelihood ratio tests showed that adding the city dummy variables could significantly improve performance of our models. We also estimated models with and without the city dummy variables and found that most of the dummy variables returned highly significant coefficients. The incidental problem,[48] which can endanger the use of regional dummy variables, was not a concern for our study because we set infill asymptotics with a very large sample size and a small, fixed number of city dummy variables.[49]

We hypothesized that the demographic and socioeconomic variables would exert an indirect effect on exposure after controlling for transportation, land use, employment, and parcel-level characteristics. That is, although these factors are not as directly associated with traffic generation as the infrastructure and land use factors that we hypothesized to have direct effects, they could influence nearby housing affordability, community resources and cultural amenities, and residential location choices. We derived a parcel's neighborhood characteristics using the most localized geographic scale available from the census. We obtained a parcel's neighborhood racial/ethnic composition from the 2010 US Census BG data and obtained its socioeconomic indicators (including poverty, home ownership, and foreign-born status) from 2005–2009 US Census American Community Survey tract data.

Spatial Regression Methodology

We used spatial regression models to assess associations between exposure and socioeconomic variables after controlling for confounding variables, not to infer causality.[36] Quantitative environmental justice studies have traditionally used ordinary least squares regression to evaluate community impacts of environmental hazards, but the use of spatial modeling techniques is becoming more common in environmental justice research because of their ability to address problems of spatial autocorrelation.[30,31,50] Spatial autocorrelation occurs when the values of one area are influenced by the values of their neighbors, violating the assumptions of independence that ordinary least squares regression assumes. We tested the model residuals for spatial autocorrelation using the univariate Moran's I and found spatial autocorrelation for all models. Next we ran the Lagrange multiplier diagnostic test to determine the spatial regression technique that was most appropriate for addressing spatial autocorrelation. Spatial lag models can be used to address spatial dependence in the dependent variable, and spatial error models can be used to address spatial dependence in the error terms.[32,33]

Both the Lagrange multiplier lag test statistic and Lagrange multiplier error test statistic suggested that spatial dependence effects may exist in both the dependent variable and the error terms for all 3 models (total VMT, truck VMT, and vehicle PM). Moreover, the robust versions of the Lagrange multiplier lag and error tests suggested that an appropriate approach for truck VMT and vehicle PM should account for potential threats of spatial autocorrelation in both the dependent variable and the error terms. This test did not indicate that spatial dependence in the error terms was a problem for the total VMT model. We did, however, estimate separate spatial lag and spatial error models for all dependent variables to understand the sensitivity of results over different modeling techniques. For consistency, the final spatial regression model reported in the Results section for all dependent variables used the Cliff-Ord approach, which adjusts for spatial dependence in both the dependent variables and the error terms.[51,52] This modeling approach takes the following form:

$$(1)\quad \begin{cases} \mathbf{Y} = \lambda \mathbf{WY} + \mathbf{X}\boldsymbol{\beta} + \varepsilon \\ \varepsilon = \rho \mathbf{W}\varepsilon + \mathbf{u} \end{cases},$$

where

- $\mathbf{Y}$ is an $n \times 1$ vector of the dependent variable, and n is the total number of observations in the sample;
- $\mathbf{W}$ is an $n \times n$ spatial weight matrix, which describes the pattern of spatial dependent effects;
- $\mathbf{X}$ is an $n \times k$ matrix of independent variables, and k is the total number of independent variables;
- ε is an $n \times 1$ vector of original error terms in which spatial dependence is not taken account of;

TABLE 1—Study Area and Subarea Demographic and Socioeconomic Characteristics, Census Block Groups: Southern Los Angeles County, CA, 2005–2010.

Characteristic	Carson	Los Angeles, San Pedro	Los Angeles, Wilmington	Long Beach, North	Long Beach, South	Long Beach, West
Population density (persons/square mile)[a]	4991	11 082	7746	14 884	25 377	8602
Racial/ethnic composition, %[a]						
Non-Hispanic White (single race)	13	45	14	12	14	5
Non-Hispanic Black (single race)	8	5	4	17	14	12
Non-Hispanic API (single race)	34	5	9	24	13	32
Hispanic	39	36	68	39	54	41
Socioeconomic and housing characteristics (tract), 2005–2009, %						
Foreign-born persons	39	20	35	36	37	49
Persons in poverty	6	11	18	23	31	14
Owner-occupied housing units	83	50	51	41	18	55
Parcel characteristics						
Multifamily residential parcel type (1/0)	3	27	22	30	67	15
Structure built before 1960 (1/0)	59	77	68	87	86	87
Land use type of parcels (within 250 m)						
% area residential	77	77	68	76	71	76
% area commercial	3	4	6	8	12	3
Mixed-use area (1/0)[b]	1	2	2	5	10	0
Roadway type within 250 m						
Truck route miles	0.08	0.02	0.05	0.01	0.00	0.09
Major (nontruck) route miles	0.29	0.73	0.52	0.57	0.89	0.48
Nearby employment, 2008 (BG)						
Jobs per square mile/1000	2.1	1.8	2.2	3.2	3.6	1.2
% jobs in neighborhood businesses	48	50	49	46	51	51
Exposures						
Mean total VMT/100 (within 250 m)	90.1	80.5	87.4	106.4	122.8	183.3
Mean truck VMT/100 (within 250 m)	4.1	2.4	2.9	2.9	2.2	25.7
Mean vehicle PM (parcel level, $\mu m/m^3$)	3.9	1.9	2.8	5.8	3.6	7.0

Note. API = Asian/Pacific Islander; BG = block group; PM = particulate matter; VMT = vehicle miles traveled.
[a]Relates to 2010 BG.
[b]Mixed use was defined as > 25% residential and > 25% commercial.

- $\mathbf{u} \sim N(0, \sigma^2 \mathbf{I}_n)$ is an $n \times 1$ vector of error terms in which spatial dependence effects are taken account of; and
- λ and ρ are spatial coefficients.

We implemented the Cliff-Ord model using the R Project "sphet" package (Gianfranco Piras, Ithaca, NY),[53] and we used modeling methodologies previously described.[54–56] The model implementation relies on the instrumental variables and the generalized moments of methods estimators. We did not chose the maximum likelihood estimators because the Monte Carlo simulation of Arraiz et al.[54] suggests that the maximum likelihood estimator can be substantially biased if the error terms are heteroskedastic. We relied on the commonly used Delaunay triangulation technique to create the spatial weight matrix that defines the spatial dependence effects among sample observations. Neighbors sharing a Delaunay triangle with one parcel have equal weights of impact on this parcel. We experimented with other forms of spatial weight matrices and obtained similar results.

RESULTS

The study area contains substantial racial/ethnic and socioeconomic diversity, and understanding population distributions in the study area in relation to major roadways and truck routes provides important context for assessing potential disparities in exposure. The 2010 US Census data indicated that the study area was home to more than 370 000 residents and had a population density greater than that of the county as a whole (about 10 300 vs 2405 persons/square mile). The densest study subareas were the northern and southern portions of Long Beach east of the I-710 freeway (Figure 1). The study area was composed of 56% Hispanic residents compared with 48% for Los Angeles County as a whole; less than one fifth (17%) of the

TABLE 2—Characteristics of Parcels by Magnitude of Exposure: Southern Los Angeles County, CA, 2005–2010

		Total VMT/100 (Within 250 m), Quartile Means				Truck VMT/100 (Within 250 m), Quartile Means				Vehicle PM (Parcel Level), Quartile Means			
Characteristics	All	1st	2nd	3rd	4th	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Total parcels	46 242	11 560	11 561	11 561	11 560	11 560	11 561	11 561	11 560	11 560	11 561	11 560	11 561
Direct factors: built environment characteristics													
Roadway type within 250 m													
Truck route miles	0.038	0.005	0.025	0.040	0.084	0.000	0.004	0.009	0.141	0.014	0.038	0.036	0.065
Major (nontruck) route miles	0.597	0.397	0.574	0.663	0.755	0.424	0.661	0.705	0.598	0.635	0.577	0.619	0.558
Parcel use type													
% area residential	0.740	0.775	0.782	0.724	0.680	0.784	0.789	0.737	0.651	0.767	0.746	0.699	0.748
% area commercial	0.056	0.012	0.032	0.069	0.110	0.012	0.043	0.071	0.097	0.021	0.054	0.084	0.063
Mixed use (1/0) (> 25% residential and > 25% commercial)	0.032	0.003	0.004	0.024	0.095	0.003	0.007	0.034	0.083	0.006	0.016	0.068	0.037
Nearby employment (BG)													
Jobs per square mile/1000	2.276	1.642	1.995	2.560	2.909	1.678	2.209	2.589	2.631	1.359	2.532	2.730	2.485
% neighborhood jobs	0.491	0.513	0.472	0.487	0.494	0.502	0.486	0.483	0.494	0.489	0.482	0.496	0.499
Parcel characteristics													
Multifamily residential parcel type (1/0)	0.269	0.115	0.230	0.336	0.393	0.130	0.300	0.342	0.303	0.185	0.346	0.320	0.223
Structure built before 1960 (1/0)	0.761	0.708	0.787	0.787	0.763	0.736	0.804	0.749	0.756	0.724	0.744	0.737	0.841
Indirect factors: demographic and socioeconomic characteristics													
Nearby racial/ethnic composition (BG), %													
Non-Hispanic Black, 2010 (single race)	0.085	0.066	0.074	0.092	0.108	0.073	0.081	0.096	0.090	0.034	0.061	0.107	0.137
Non-Hispanic API, 2010 (single race)	0.160	0.174	0.164	0.140	0.162	0.178	0.138	0.160	0.165	0.045	0.120	0.218	0.257
Hispanic, 2010	0.469	0.446	0.434	0.479	0.518	0.431	0.454	0.426	0.566	0.363	0.583	0.502	0.429
Nearby socioeconomic status, 2005–2009 (tract), %													
Poverty	0.162	0.117	0.151	0.185	0.196	0.123	0.170	0.169	0.187	0.090	0.179	0.204	0.175
Home ownership	0.501	0.625	0.524	0.437	0.417	0.602	0.469	0.451	0.482	0.571	0.457	0.479	0.496
Foreign-born	0.334	0.328	0.320	0.326	0.360	0.326	0.312	0.321	0.376	0.205	0.349	0.379	0.402

Note. API = Asian-Pacific Islander; BG = block group; PM = particulate matter; VMT = vehicle miles traveled.

TABLE 3—Multivariate Analysis of Exposure, Residential Parcels: Southern Los Angeles County, CA, 2005–2010

Independent Variables	Total VMT/100 (Within 250 m), Model 1, Coefficient	Truck VMT/100 (Within 250 m), Model 2, Coefficient	Vehicle PM (Parcel Level), Model 3, Coefficient
Intercept	−33.42**	−12.15***	1.05***
Direct factors: built environment characteristics			
Roadway type (within 250 m)			
Truck route miles/100	711.95***	86.11***	7.10***
Major (nontruck) route miles/100	163.00***	7.47***	0.85***
Land use type of parcels (within 250 m)			
% area residential	12.38	6.32***	−0.21
% area commercial	182.37***	−0.90	−1.02*
Mixed-use area (1/0)[a]	−2.59	0.80**	0.13**
Nearby employment, 2008 (BG)			
Jobs per square mile/1000	−0.60***	−0.07***	−0.01**
% jobs in neighborhood businesses	−11.60***	−1.12*	−0.08
Parcel characteristics			
Multifamily residential parcel type (1/0)	−0.81	−0.08	−0.02*
Structure built before 1960 (1/0)	−0.88	0.08	0.03**
Indirect factors: demographic and socioeconomic characteristics			
Nearby racial/ethnic composition, 2010 (BG), %			
Non-Hispanic Black (single race)	193.04***	19.83***	3.18***
Non-Hispanic API (single race)	58.17***	−1.77	1.42***
Hispanic	−37.63***	−2.22	0.76***
Nearby socioeconomic status, 2005–2009 (tract), %			
Poverty	−101.59***	7.46	−1.54***
Home ownership	−2.19	5.24***	−0.23
Foreign-born	−40.68*	−0.12	0.65
Municipal subareas[b]			
Los Angeles, Wilmington area (1/0)	32.43***	0.31	0.51***
Long Beach, western area (1/0)	96.85***	22.11***	5.24***
Long Beach, northern area (1/0)	42.12***	−1.74	3.02***
Long Beach, southern area (1/0)	24.50***	−0.18	1.47***
Carson (1/0)	4.84	−4.28**	0.97***
Spatial lag coefficient on dependent variable (λ)	0.01	0.00	−0.09***
Spatial lag coefficient for errors (ρ)	0.90***	0.90***	0.90***

Note. API = Asian-Pacific Islander; BG = block group; PM = particulate matter; VMT = vehicle miles traveled. We have reported the direct effect coefficients (β in equation 1) for these Cliff-Ord models. According to Li and Saphores[55] and Saphores and Li,[56] the direct effect coefficients are very similar to the total effect coefficients in spatial regression models. The sample size was n = 46 242 parcels.

[a]Mixed use was defined as > 25% residential and > 25% commercial.

[b]The San Pedro area is the excluded reference category.

*P < .05; **P < .01; ***P < .001.

residents were non-Hispanic White compared with almost one third (28%) for the county (Table 1). The Wilmington area of Los Angeles had the highest composition of Hispanic residents (75%), and the San Pedro area of Los Angles had the highest composition of non-Hispanic Whites (37%).

According to 2005–2009 US Census data, about 16% of residents in the study area had an income below the federal poverty level (vs 15% for the county) and about 33% of residents were foreign-born (vs 35% for the county). The southern area of Long Beach had the highest poverty level, the lowest home-ownership rate, the highest percentage of multifamily parcels, and parcels with the highest percentage of nearby commercial uses (Table 1). By contrast, the Carson area had the lowest poverty level, the highest homeownership rate, and the lowest percentage of structures built before 1960. These factors could be related to potential exposures because multifamily parcels and nearby commercial uses and employment centers could be associated with greater nearby traffic generation; also, multifamily and older housing structures may have higher rates of indoor exposure to outdoor pollutants.[46] Parcels in Carson and Long Beach had the highest levels of nearby truck routes, whereas the San Pedro area of Los Angeles and the southern portion of

Long Beach had the highest level of nontruck roadways.

Descriptive Results

Although the parcel exposure measures were significantly correlated (0.59–0.67), their spatial distribution varied across the study area in ways that could differentially affect nearby populations. The highest total VMT exposures occurred in the Long Beach study areas, perhaps because of proximity to the I-710 freeway (Table 1). The highest truck VMT exposures occurred in the western Long Beach study area, which has major truck routes on its western and eastern boundaries. Western and northern Long Beach had the highest levels of parcel-level vehicle PM exposures.

As expected, the means of nearby truck route miles increased sizably from parcels in the lowest exposure quartile to those in the highest quartile for all exposure metrics, but this did not hold for nontruck roadway miles (Table 2). Parcels in the highest quartile for both traffic exposure measures had lower residential use and higher commercial use and job density, but these patterns did not hold for vehicle PM exposure.

Parcels in the highest quartile for both traffic exposure measures consistently had a higher percentage of nearby Black, Hispanic, and poor residents. Parcels in the highest quartile for vehicle PM exposure had a higher percentage of nearby Black and Asian/Pacific Islander (API) residents, but this pattern did not hold for the percentage of Hispanic and poor residents. Parcels in the lowest quartile for all exposure metrics had higher home ownership, and those in the highest quartile had a higher percentage of foreign-born residents.

Spatial Regression Results

We specified 6 regression models to assess potential racial/ethnic and socioeconomic disparities in exposure after accounting for land use, built environment, and infrastructure factors that could be associated with traffic generation (Table 3). For each dependent variable (total VMT, truck VMT, and vehicle PM), we have reported a Cliff-Ord model that accounts for spatial autocorrelation in both the dependent variables and the error terms. The λ and ρ variables in the Cliff-Ord models were statistically significant.

As expected, more nearby roadway and truck route mileage was associated with higher exposure for all measures. More nearby commercial land use was associated with higher total VMT exposure but unexpectedly lower vehicle PM exposure. More residential land use was associated with higher truck VMT exposure. Nearby mixed land use was associated with higher truck VMT and vehicle PM exposure, but more nearby neighborhood-serving businesses were associated with lower traffic exposure. Unlike descriptive results, parcels with more nearby job density were associated with lower exposure after controlling for other factors.

After controlling for nearby built environment factors that could be associated with traffic generation, parcels in BGs with a higher percentage of Black residents were associated with higher exposures for all exposure measures, a higher percentage of nearby API residents was associated with higher VMT and vehicle PM exposure, and a higher percentage of nearby Hispanics was associated with higher vehicle PM exposure. Contrary to descriptive results, however, a higher percentage of Hispanic, poor, and foreign-born residents was associated with lower total VMT exposure after controlling for other factors. Higher home ownership was associated with higher truck VMT exposure, and more nearby poverty was associated with lower vehicle PM exposure.

DISCUSSION

We found racial/ethnic disparities in traffic and vehicle PM exposure in a major goods movement corridor after controlling for built environment and land use factors associated with traffic generation, particularly for parcels with a higher percentage of nearby non-Hispanic Black and API residents. Interestingly, a higher percentage of nearby Hispanic residents was associated with higher total VMT exposure but lower vehicle PM exposure, suggesting racial/ethnic disparities are nuanced depending on the exposure metric used, the distribution of the emission source, and pollutant dispersal patterns.

In contrast to most available distributional studies of traffic and mobile-source air pollution exposure,[5,6,8,10] we found that lower socioeconomic status (more foreign-born and poor residents) tended to be associated with lower exposure and that higher socioeconomic status (more home ownership) tended to be associated with higher exposure. This finding, however, is in line with a handful of stationary- and mobile-source air pollution and traffic exposure studies that found little or no income-based disparity[17,57] or higher exposures for higher income or nonpoor areas.[18,19,58]

Further research is needed to investigate factors underlying disparate exposures in goods movement corridors. Transportation infrastructure, land use, and residential patterns emerged historically in the context of structural inequalities, uneven development patterns, and residential and economic segregation.[6,32] Future research should seek to understand local awareness of traffic and air pollution hazards, whether housing market constraints restrict the residential location choices of subpopulations, and whether some residents are more likely to accept higher levels of exposure to live in more affordable, accessible, or culturally diverse areas.

Nearby roadway designation may play an important role, considering that nearby truck route miles were a much stronger predictor of exposure than were nontruck roadway miles. We found some evidence that commercial strips and mixed land use areas may be associated with higher traffic and vehicle PM exposure, which raises concerns about whether policies promoting mixed-use land development could result in higher exposures.

Limitations

Our study has several limitations. Our results cannot be readily generalized, and future research is needed to assess whether similar disparities exist in other corridors with divergent population, built environment, and land use geographic patterns. We assessed population impacts on the basis of a parcel's BG and tract composition, but exposures may also vary systematically by the characteristics of parcel residents. Lastly, our vehicle PM exposure measure may underestimate cumulative parcel air pollution exposures because it does not account for nonvehicle sources, such as petroleum refineries and idling cargo ships and pollution transported from other regions.

Conclusions

Despite these limitations, this study makes several contributions to the environmental justice literature. First, it stresses the importance of understanding environmental disparities in transportation and goods movement corridors in ways that inform infrastructure and land use planning. Second, we have provided the first assessment to our knowledge of exposure disparities at the parcel level, a more geographically refined spatial resolution more appropriate for examining near-roadway impacts. Third, we used 3 metrics of exposure that reflect geographic differences in emission sources and pollutant dispersion patterns. Fourth, we used spatial regression techniques to account for spatial autocorrelation in our assessment of environmental inequities.

Our results raise concerns that planning and policy mechanisms to lower ambient air pollution levels will likely not be sufficient to protect those most exposed to mobile-source pollution. ■

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Contributors

D. Houston was primarily responsible for the study conceptualization and design, analysis, and writing of the article. W. Li conducted the spatial regression modeling and contributed to the interpretation of results and writing. J. Wu conducted the modeling of vehicle particulate matter and contributed to the analysis and writing.

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Human Participant Protection

No protocol approval was needed for this study because it relied on secondary data containing no personal identifying information.

References

1. Adar SD, Kaufman JD. Cardiovascular disease and air pollutants: evaluating and improving epidemiological data implicating traffic exposure. *Inhal Toxicol.* 2007;19(suppl 1):135–149.

2. Lipfert FW, Wyzga RE. On exposure and response relationships for health effects associated with exposure to vehicular traffic. *J Expo Sci Environ Epidemiol.* 2008;18(6):588–599.

3. Wu J, Ren C, Delfino RJ, Chung J, Wilhelm M, Ritz B. Association between local traffic-generated air pollution and preeclampsia and preterm delivery in the south coast air basin of California. *Environ Health Perspect.* 2009;117(11):1773–1779.

4. Bae C-HC, Sandlin G, Bassok A, Kim S. The exposure of disadvantaged populations in freeway air-pollution sheds: a case study of the Seattle and Portland regions. *Environ Plann B Plann Des.* 2007;34(1):154–170.

5. Gunier RB, Hertz A, Von Behren J, Reynolds P. Traffic density in California: socioeconomic and ethnic differences among potentially exposed children. *J Expo Anal Environ Epidemiol.* 2003;13(3):240–246.

6. Houston D, Wu J, Ong P, Winer A. Structural disparities of urban traffic in southern California: implications for vehicle-related air pollution exposure in minority and high-poverty neighborhoods. *J Urban Aff.* 2004;26(5):565–592.

7. O'Neill MS, Jerrett M, Kawachi I, et al. Health, wealth, and air pollution: advancing theory and methods. *Environ Health Perspect.* 2003;111(16):1861–1870.

8. Schweitzer L, Valenzuela AJ. Environmental injustice and transportation: the claims and the evidence. *J Plann Lit.* 2004;18(4):383–398.

9. Laurent O, Bard D, Filleul L, Segala C. Effect of socioeconomic status on the relationship between atmospheric pollution and mortality. *J Epidemiol Community Health.* 2007;61(8):665–675.

10. Ponce NA, Hoggatt KJ, Wilhelm M, Ritz B. Preterm birth: the interaction of traffic-related air pollution with economic hardship in Los Angeles neighborhoods. *Am J Epidemiol.* 2005;162(2):140–148.

11. Fisher JB, Kelly M, Romm J. Scales of environmental justice: combining GIS and spatial analysis for air toxics in West Oakland, California. *Health Place.* 2006;12(4):701–714.

12. Houston D, Krudysz M, Winer A. Diesel truck traffic in port-adjacent low-income and minority communities; environmental justice implications of near-roadway land use conflicts. *J Transportation Research Board.* 2008;2067:38–46.

13. Anderton DL, Anderson AB, Oakes JM, Fraser MR. Environmental equity: the demographics of dumping. *Demography.* 1994;31(2):229–248.

14. Baden BM, Noonan DS, Turaga RMR. Scales of justice: is there a geographic bias in environmental equity analysis? *J Environ Plann Manage.* 2007;50(2):163–185.

15. Mohai P, Saha R. Reassessing racial and socioeconomic disparities in environmental justice research. *Demography.* 2006;43(2):383–399.

16. Ringquist EJ. Assessing evidence of environmental inequities: a meta-analysis. *J Policy Anal Manage.* 2005;24(2):223–247.

17. Goodman A, Wilkinson P, Stafford M, Tonne C. Characterising socio-economic inequalities in exposure to air pollution: a comparison of socio-economic markers and scales of measurement. *Health Place.* 2011;17(3):767–774.

18. Gouveia N, Fletcher T. Time series analysis of air pollution and mortality: effects by cause, age and socioeconomic status. *J Epidemiol Community Health.* 2000;54(10):750–755.

19. Havard S, Reich BJ, Bean K, Chaix B. Social inequalities in residential exposure to road traffic noise: an environmental justice analysis based on the RECORD cohort study. *Occup Environ Med.* 2011;68(5):366–374.

20. Schweitzer L, Stephenson MJ. Right answers, wrong questions: environmental justice as urban research. *Urban Stud.* 2007;44(2):319–337.

21. Most MT, Sengupta R, Burgener MA. Spatial scale and population assignment choices in environmental justice analyses. *Prof Geogr.* 2004;56(4):574–586.

22. Cutter SL, Holm JD, Clark L. The role of geographic scale in monitoring environmental justice. *Risk Anal.* 1996;16(4):517–526.

23. Hu S, Fruin S, Kozawa K, Mara S, Paulson SE, Winer AM. A wide area of air pollutant impact downwind of a freeway during pre-sunrise hours. *Atmos Environ.* 2009;43(16):2541–2549.

24. Karner AA, Eisinger DS, Niemeir D. Near-roadway air quality: synthesizing the findings from real-world data. *Environ Sci Technol.* 2010;44(14):5334–5344.

25. Zhou Y, Levy JI. Factors influencing the spatial extent of mobile source air pollution impacts: a meta-analysis. *BMC Public Health.* 2007;7:89.

26. Zhu Y, Hinds WC, Kim S, Shen S, Sioutas C. Study of ultrafine particles near a major highway with heavy-duty diesel traffic. *Atmos Environ.* 2002;36:4323–4335.

27. California Air Resources Board. *Harbor Community Monitoring Study.* Sacramento, CA: California Air Resources Board; 2007.

28. Port of Los Angeles. *Port of Los Angeles Baseline Transportation Study.* Los Angeles, CA: Port of Los Angeles; 2004.

29. Setton EM, Hystad PW, Keller CP. Opportunities for using spatial property assessment data in air pollution exposure assessments. *Int J Health Geogr.* 2005;4(1):26–33.

30. Chakraborty J, Maantay JA, Brender JD. Disproportionate proximity to environmental health hazards: methods, models, and measurement. *Am J Public Health.* 2011;101(suppl 1):S27–S36.

31. Maantay J. Asthma and air pollution in the Bronx: methodological and data considerations in using GIS for environmental justice and health research. *Health Place.* 2007;13(1):32–56.

32. Pastor M, Morello-Frosch R, Sadd JL. The air is always cleaner on the other side: race, space, and ambient air toxics exposures in California. *J Urban Aff.* 2005;27(2):127–148.

33. Grineski SE, Collins TW, Ford P, et al. Climate change and environmental injustice in a bi-national context. *Appl Geogr.* 2012;33(1):25–35.

34. Los Angeles County Tax Assessor. *Parcel Attribute and Sales Data.* Los Angeles, CA: Los Angeles County Tax Assessor; 2010.

35. Houston D, Jaimes G, Ong P, Winer A. Traffic exposure near the Los Angeles–Long Beach port complex: using GPS-enhanced tracking to assess the implications of unreported travel and locations. *J Transp Geogr.* 2011;19(6):1399–1409.

36. Jerrett M, Burnett RT, Kanaroglou P, et al. A GIS—environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environ Plan A*. 2001;33(6):955–973.

37. Wu J, Houston D, Lurmann F, Ong P, Winer A. Exposure of PM2.5 and EC from diesel and gasoline vehicles in communities near the ports of Los Angeles and Long Beach, California. *Atmos Environ*. 2009;43(12):1962–1971.

38. California Air Resources Board. *Executive Summary for the Proposed Identification of Diesel Exhaust as a Toxic Air Contaminant*. Sacramento, CA: California Air Resources Board; 1998.

39. Watson JG, Chow JC, Chen L-WA, et al. Particulate emission factors for mobile fossil fuel and biomass combustion sources. *Sci Total Environ*. 2011;409(12):2384–2396.

40. South Coast Air Quality Management District. *Multiple Air Toxics Exposure Study in the South Coast Air Basin—MATES-II*. Diamond Bar, CA: South Coast Air Quality Management District; 1999.

41. Jerrett M, Arain A, Kanaroglou P, et al. A review and evaluation of intraurban air pollution exposure models. *J Expo Anal Environ Epidemiol*. 2005;15:185–204.

42. Benson P. *CALINE4: A Dispersion Model for Predicting Air Pollutant Concentrations Near Roadways*. Sacramento, CA: California Department of Transportation; 1989.

43. Ryan PH, LeMasters GL. A review of land-use regression models for characterizing intraurban air pollution exposure. *Inhal Toxicol*. 2007;19(suppl 1):127–133.

44. Jerrett M, Burnett RT, Brook J, et al. Do socioeconomic characteristics modify the short term association between air pollution and mortality? Evidence from a zonal time series in Hamilton, Canada. *J Epidemiol Community Health*. 2004;58(1):31–40.

45. Boarnet MG, Joh K, Siembab W, Fulton W, Nguyen M. Retrofitting the suburbs to increase walking: evidence from a land use–travel study. *Urban Stud*. 2011;48(1):129–159.

46. Adamkiewicz G, Zota AR, Fabian MP, et al. Moving environmental justice indoors: understanding structural influences on residential exposure patterns in low-income communities. *Am J Public Health*. 2011;101(suppl 1):S238–S245.

47. Tiebout C. A pure theory of local expenditures. *J Polit Econ*. 1956;64(5):416–424.

48. Neyman J, Scott EL. Consistent estimates based on partially consistent observations. *Econometrica*. 1948;16(1):1–32.

49. Lee L-F, Yu J. Estimation of spatial autoregressive panel data models with fixed effects. *J Econom*. 2010;154(2):165–185.

50. Chun Y, Kim Y, Campbell H. Using Bayesian methods to control for spatial autocorrelation in environmental justice research: an illustration using toxics release inventory data for a Sunbelt county. *J Urban Affairs*. 2012;34(4):419–439.

51. Cliff AD, Ord JK. *Spatial Autocorrelation*. London, UK: Pion; 1973.

52. Cliff AD, Ord JK. *Spatial Processes, Models and Applications*. London, UK: Pion; 1981.

53. Piras G. sphet: spatial models with heteroskedastic innovations in R. *J Stat Softw*. 2010;35(1):1–21.

54. Arraiz I, Drukker DM, Kelejian HH, Prucha IR. A spatial Cliff-Ord-type model with heteroscedastic innovations: small and large sample results. *J Reg Sci*. 2010;50(2):592–614.

55. Li W, Saphores JD. A spatial hedonic analysis of the value of urban land cover in the multifamily housing market in Los Angeles, CA. *Urban Stud*. 2011;49(12):2597–2615.

56. Saphores JD, Li W. Estimating the value of urban green areas: a hedonic pricing analysis of the single family housing market in Los Angeles, CA. *Landsc Urban Plan*. 2012;104(3–4):373–387.

57. Bowen WM, Salling MJ, Haynes KE, Cyran EJ. Toward environmental justice: spatial equity in Ohio and Cleveland. *Ann Assoc Am Geogr*. 1995;85(4):641–663.

58. Jerrett M, Eyles J, Cole D, Reader S. Environmental equity in Canada: an empirical investigation into the income distribution of pollution in Ontario. *Environ Plan A*. 1997;29(10):1777–1800.