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Race/Ethnicity, Socioeconomic Status, Residential Segregation, and Spatial Variation in Noise Exposure in the Contiguous United States

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BACKGROUND: Prior research has reported disparities in environmental exposures in the United States, but, to our knowledge, no nationwide studies have assessed inequality in noise pollution.

OBJECTIVES: We aimed to *a*) assess racial/ethnic and socioeconomic inequalities in noise pollution in the contiguous United States; and *b*) consider the modifying role of metropolitan level racial residential segregation.

METHODS: We used a geospatial sound model to estimate census block group–level median (L_{50}) nighttime and daytime noise exposure and 90th percentile (L_{10}) daytime noise exposure. Block group variables from the 2006–2010 American Community Survey (ACS) included race/ethnicity, education, income, poverty, unemployment, homeownership, and linguistic isolation. We estimated associations using polynomial terms in spatial error models adjusted for total population and population density. We also evaluated the relationship between race/ethnicity and noise, stratified by levels of metropolitan area racial residential segregation, classified using a multigroup dissimilarity index.

RESULTS: Generally, estimated nighttime and daytime noise levels were higher for census block groups with higher proportions of nonwhite and lower-socioeconomic status (SES) residents. For example, estimated nighttime noise levels in urban block groups with 75% vs. 0% black residents were 46.3 A-weighted decibels (dBA) [interquartile range (IQR): 44.3–47.8 dBA] and 42.3 dBA (IQR: 40.4–45.5 dBA), respectively. In urban block groups with 50% vs. 0% of residents living below poverty, estimated nighttime noise levels were 46.9 dBA (IQR: 44.7–48.5 dBA) and 44.0 dBA (IQR: 42.2–45.5 dBA), respectively. Block groups with the highest metropolitan area segregation had the highest estimated noise exposures, regardless of racial composition. Results were generally consistent between urban and suburban/rural census block groups, and for daytime and nighttime noise and robust to different spatial weight and neighbor definitions.

CONCLUSIONS: We found evidence of racial/ethnic and socioeconomic differences in model-based estimates of noise exposure throughout the United States. Additional research is needed to determine if differences in noise exposure may contribute to health disparities in the United States. <https://doi.org/10.1289/EHP898>

Introduction

A growing body of evidence links environmental noise—a biologic stressor usually generated by mechanized sources: transportation, industry, power generation, power tools, and air-conditioning—to hearing loss and other health outcomes (Basner et al. 2014). The human body initially reacts to noise with activation of the central nervous system, even while asleep. This can result in release of stress hormones and increased blood pressure, heart rate, and cardiac output (Evans et al. 1995; Lercher 1996). While individual noise sensitivities differ, the World Health Organization (WHO) estimated a “no observed effect level” for average outdoor nighttime noise of 30 A-weighted decibels (dBA) based on evidence that sleep is not disturbed by noise below 30 (dBA) (WHO 2009). The Federal Highway

Administration noise abatement criteria near hospitals and schools is 70 dBA, a recommendation that balances health, communication, and economic interests (U.S. DOT 2015). Exposure to these noise levels has been associated with impaired cognitive performance (Clark et al. 2012) and behavioral problems in children (Hjortebjerg et al. 2016), as well as hypertension (van Kempen and Babisch 2012), type 2 diabetes (Sørensen et al. 2013), cardiovascular disease (Gan et al. 2012), and reduced birth weight (Gehring et al. 2014). The WHO (2011) has estimated >1 million disability adjusted life years are lost annually in Western Europe due to environmental noise, attributable primarily to annoyance and sleep disturbance. The WHO calculation was based on estimated noise exposures and previous research on associations between noise and health outcomes.

Environmental noise is typically measured as sound pressure level, a logarithmic quantity expressed in decibels (dB); for example, an increase of 3 dB is a doubling of sound energy. With every 5.5-dB increase, the proportion of individuals highly annoyed by residential noise exposure appears to double (ANSI 2003). Measurements of sound pressure level are commonly adjusted by A-weighting to reflect how humans perceive sound across frequency, denoted as dBA (Murphy and King 2014). Because sound levels vary over time, metrics describing the statistical behavior of the variation are utilized. The energy average, or equivalent, indicator is abbreviated L_{eq} . Multiple exceedance levels are used to characterize magnitude, rate of occurrence, and duration of environmental noise. The L_{50} is the noise level exceeded half of the time, whereas the L_{10} is the level exceeded 10% of the time.

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Like other exposures, the impact of noise varies by intensity, duration, and frequency. Noise sensitivity or degree of reactivity to the same level of noise can differ from person to person and by source of noise (Janssen et al. 2011; van Kamp et al. 2004). Time of day may also play a role, such that associations between noise and health outcomes appear to be stronger for noise exposure during the night vs. day (Basner et al. 2014). Despite evidence of noise-related adverse health effects, the most recent nationwide noise pollution estimates were made by the U.S. Environmental Protection Agency (U.S. EPA) in 1981 (Simpson and Bruce 1981). By extrapolating the U.S. EPA's 1981 estimate of the prevalence of noise exposure to the current U.S. population, Hammer et al. (2014) estimated that 145.5 million Americans experience annual noise levels that exceed those recommended to protect public health with an adequate margin of safety. Moreover, the distribution of noise is not uniform across communities, and some groups may have heightened vulnerability to noise (van Kamp and Davies 2013). The spatial distribution of noise exposure may contribute to health disparities seen in the United States and elsewhere.

A body of environmental justice literature from the United States suggests that air pollution and exposure to hazardous waste often follows a social gradient such that racial/ethnic minorities, the poor, and the undereducated endure greater exposure (Bell and Ebisu 2012; Hajat et al. 2015; Mohai and Saha 2007). A more limited body of scholarship from Europe frames environmental injustices by social categories, but not usually race/ethnicity, finding, for example, that those in the 10% most deprived areas in England are the most exposed to chemical, metal, and waste facilities (Laurent 2011; Walker et al. 2005). Researchers theorize that in the United States, communities of color and the poor are disproportionately exposed to environmental hazards due to a variety of factors, including weak regulatory enforcement in marginalized neighborhoods and lack of capacity to engage in land use decision-making, which may contribute to the concentration of potentially hazardous mobile and stationary emission sources in these communities (Morello-Frosch 2002; Pulido 2000).

Only a few studies have evaluated community-level inequality in exposure to estimated noise pollution. Studies in Minneapolis and St. Paul, Minnesota (Nega et al. 2013) and Montreal, Quebec, Canada (Carrier et al. 2016; Dale et al. 2015) found that lower neighborhood socioeconomic status (SES) or a higher proportion of minority race/ethnicities was associated with higher noise levels. Outside the United States and Canada, results have been mixed and more focused on SES than race/ethnicity as an explanatory variable. In Hong Kong, Lam and Chan (2008) reported a weak, but statistically significant, association between lower income and educational attainment and higher noise exposure at the street block level. Haines et al. (2002) estimated noise exposure at 123 schools near the Heathrow Airport in the United Kingdom, and found in a subanalysis that a higher proportion of students eligible for free lunch was associated with higher noise exposure. In nearby Birmingham, a higher proportion of black residents at the enumeration district level was weakly associated with estimated daytime noise levels (Brainard et al. 2004). In Marseilles, France, census blocks with intermediate levels of deprivation had the highest estimated exposure to road noise, whereas in Berlin, Germany, there was no straightforward association between SES and noise exposure at the planning unit level (Lakes et al. 2014).

At the individual level, one study in Wales, United Kingdom (Poortinga et al. 2008) and another in Germany (Kohlhuber et al. 2006) found that lower SES participants reported more neighborhood noise. However, in Paris, France, individuals living in

neighborhoods with the highest housing values and highest levels of educational attainment also had the highest estimated noise exposures (Havard et al. 2011).

To our knowledge, no prior studies have evaluated demographic disparities in noise pollution across the United States or considered how racial segregation (an indicator of metrowide social inequality) is associated with overall noise levels. Prior U.S.-based studies have found increased racial segregation associated with more air pollution (Bravo et al. 2016; Jones et al. 2014), ambient air toxins (Morello-Frosch and Jesdale 2006; Rice et al. 2014), and less tree canopy cover (Jesdale et al. 2013). In highly segregated metropolitan areas in the United States, political power is asymmetrical along racial, ethnic, and economic lines. Further, segregation spatially binds communities of color and working class residents through the concentration of poverty, lack of economic opportunity, and exclusionary housing development and lending policies (Massey and Denton 1993). These power differences may lead to disparities in environmental hazard exposures, including noise, as more powerful residents influence decisions about the siting of undesirable land uses in ways that are beneficial to them (Cushing et al. 2015; Morello-Frosch and Lopez 2006). Because segregation can make it easier for more powerful communities to displace hazardous land uses onto disadvantaged communities where regulations may not be consistently enforced, this scenario can lead to higher pollution overall (Ash et al. 2013). Segregation may also lead to spatial segmentation between neighborhoods, workplaces, and basic services, resulting in more driving, longer commute times, and higher levels of mobile source pollution (Ash et al. 2013; Morello-Frosch and Jesdale 2006).

In the present study, we utilized a nationwide noise model (Mennitt and Fristrup 2016) to a) estimate differences in noise exposure along racial/ethnic and socioeconomic lines; and to b) examine whether segregation modifies the association between race/ethnicity and noise exposure across the contiguous United States.

Methods

We conducted a cross-sectional analysis to investigate the spatial distribution of demographic characteristics at the census block group level in relation to noise exposure across the contiguous United States. Prior work identified U.S. block group-level socioeconomic measures as a relevant spatial scale for measuring socioeconomic inequality (Krieger et al. 2003). In 2010, the study area (i.e., the contiguous United States) contained 216,331 block groups—statistical divisions of census tracts generally containing 600 to 3,000 people—that we assigned to 933 Core Based Statistical Areas (CBSAs) based on the location of their centroid, using 2010 TIGER/Line shapefiles (U.S. Census Bureau 2010a, 2010b). CBSAs are counties grouped by common commuting patterns. We excluded 1,669 block groups without residents or that were missing data on any socioeconomic variable (0.8%) and 557 block groups missing noise exposure estimates (0.3%). We then designated block groups located in CBSAs containing >100,000 people as urban ($n = 175,373$) and those located elsewhere as suburban/rural ($n = 38,732$).

Dependent Variables

Exposure to noise was based on a previously published geospatial model of environmental sound levels (Mennitt and Fristrup 2016). Similar to land use regression models of air quality, expected noise exposure was modeled using empirical acoustical data and geospatial features such as topography, climate, hydrology, and anthropogenic activity. The acoustical data included

1.5 million h of long-term (durations of ≥ 25 d at natural sites and in 14 U.S. cities, and ≥ 30 d near all U.S. airports) measurements from 492 urban and rural sites located across the contiguous United States during 2000–2014. The explanatory variables fell into seven groups (location, climatic, landcover, hydrological, anthropogenic, temporal, and equipment) and are described in detail elsewhere (Sherrill 2012). Cross-validation procedures were used to evaluate model performance and identify variables with predictive power. The method utilized random forest, a tree-based machine-learning algorithm, to perform the regression. A cross-validation procedure was used to evaluate the accuracy of national scale projections (see Table S1; Menniit and Frstrup 2016). The resulting geospatial sound model enabled mapping of ambient sound levels at 270-m resolution. We then used the zonal statistics function in ArcGIS (version 10.4; Esri) to estimate the mean sound level in each block group across the contiguous United States.

We examined three metrics of sound pressure from anthropogenic sources to assess the robustness of findings at different times of day and different levels of noise: *a*) A-weighted L_{10} (representing the loudest transient events or proximate sources) during the daytime; *b*) A-weighted L_{50} (median of the data, representing typical sound levels) during the daytime; and *c*) A-weighted L_{50} during the nighttime. All levels were projected for the summer season in order to maintain temporal consistency across noise estimates. Daytime was defined as 0700 to 1900 hours and nighttime as 1900 to 0700 hours.

Independent Variables

We used block group-level data from the 5-y 2006–2010 American Community Survey (ACS) to characterize area-level race/ethnicity and socioeconomic conditions (NHGIS Database). We used self-identified race/ethnicity to generate variables for the proportion of the population in each block group that fell in five race/ethnicity categories: Non-Hispanic American Indian, Non-Hispanic Asian, Non-Hispanic black, and Non-Hispanic white, and Hispanic (any race), referred to as American Indian, Asian, black, white, and Hispanic for the duration. Other block group-level variables included total population, population density (defined as number of people per km^2), age (defined as percent of population < 5 y old), and those selected to describe multiple dimensions of neighborhood socioeconomic context (Kawachi and Berkman 2003). We characterized neighborhood socioeconomic context at the block group level by: low educational attainment (defined as percent of adults ≥ 25 y of age with $<$ high school education), median household income (defined as block group median income in dollars in the past 12 mo), poverty (defined as percent of individuals with income below the Census Bureau poverty threshold based on family size and number of children), civilian family unemployment (defined as percent of families with ≥ 1 family member unemployed), housing tenure (defined as percent of households comprised of renters or owners), and linguistic isolation (defined as percent of households where no one > 14 y speaks English “very well”). Housing tenure may reflect residential instability as well as area-level income and wealth. Linguistically isolated households may face racial discrimination and reduced access to public services and ability to engage with regulatory processes (Gee and Ponce 2010). Some variables, like housing tenure, may have differential meaning in urban vs. rural settings, and, therefore, we conducted analyses stratified by urban/rural status (Bertin et al. 2014). To test the hypothesis that segregation was associated with higher levels of noise for all race/ethnic groups, we calculated a CBSA-level segregation measure (Sakoda 1981) for urban block groups only, using 5-y 2006–2010 ACS data (Jesdale et al. 2013). Our focus

on urban areas was aimed at facilitating comparisons with prior studies on segregation and environmental hazards (Bravo et al. 2016; Jones et al. 2014; Morello-Frosch and Jesdale 2006; Rice et al. 2014). The multigroup dissimilarity index (D_m) characterizes the residential distribution of Non-Hispanics: Asians, blacks, and whites; and Hispanics (any race) among block groups located in CBSAs. D_m ranges from 0 to 1 and represents the proportion of the racial/ethnic minority population that would need to change block groups within a metro area to achieve an even distribution (Massey and Denton 1989). Block groups located in the same CBSA received the same D_m value. We selected D_m , a metro-level indicator of social inequality, because prior research indicated that land use decision-making tends to be regionally rooted (Morello-Frosch 2002; Pastor et al. 2000).

Statistical Analysis

We used weights to extrapolate block group-level noise estimates to the individual, family, and household level across the United States. For each characteristic of interest (e.g., non-Hispanic blacks), we used the wquantile function in R (version 3.2.3; R Development Core Team) to compute the weighted 25th, 50th, and 75th percentiles of noise.

We evaluated the association between 12 socioeconomic variables and log-transformed L_{50} nighttime, L_{50} daytime, and L_{10} daytime noise exposure by specifying 12 separate regression models for each noise metric, controlled for population size and population density. We checked the residuals from ordinary least square models and found evidence of spatial autocorrelation using Moran’s I statistic ($p < 0.001$ indicating clustering; data not shown). Therefore, we implemented a spatial econometric approach in R using the spdep package (Bivand and Piras 2015). To discriminate between spatial autocorrelation in the error terms vs. the noise values themselves, we used a Lagrange multiple diagnostic test (implemented with lm.LMtests in spdep). p -values from this test suggested that a spatial error model was preferable to a spatial lag model for our data. A spatial error model specifies a linear relationship between the independent variable and the dependent variable, but unlike a traditional ordinary least squares model, errors are not assumed to be independent and identically distributed; rather, they are distributed according to a spatial autoregressive process:

$$\mathbf{y} = \beta\mathbf{X} + \mathbf{u}$$

$$\mathbf{u} = \lambda\mathbf{W}\mathbf{u} + \mathbf{e},$$

where \mathbf{y} is an $n \times 1$ vector of log L_{50} or L_{10} daytime or nighttime sound pressure, and n is the total number of block groups; \mathbf{X} is an $n \times j$ matrix of independent variables, and j is the number of independent variables; \mathbf{W} is an $n \times n$ spatial weights matrix; $\mathbf{e} \sim N(0, \sigma^2\mathbf{I})$; and λ is a spatial autoregressive coefficient (Anselin 2002). In addition to adjustment for block group population (continuous) and population density (continuous, individuals/ km^2), all models included polynomial terms for the independent variable of interest to allow for nonlinearity. We hypothesized that nonwhite race/ethnicities would experience higher overall levels of noise and steeper slopes as the percent minority increased in more segregated CBSAs. Therefore, we conducted stratified analyses [i.e., $D_m < 0.4$ (low to moderate), 0.4 to < 0.5 (high), 0.5 to < 0.6 (very high), and ≥ 0.6 (extreme)] (Jesdale et al. 2013; Morello-Frosch and Jesdale 2006) from which American Indians were excluded due to small numbers in urban areas. In all analyses, we selected the number of polynomial terms (up to 10) using likelihood ratio testing by adding polynomial terms until the

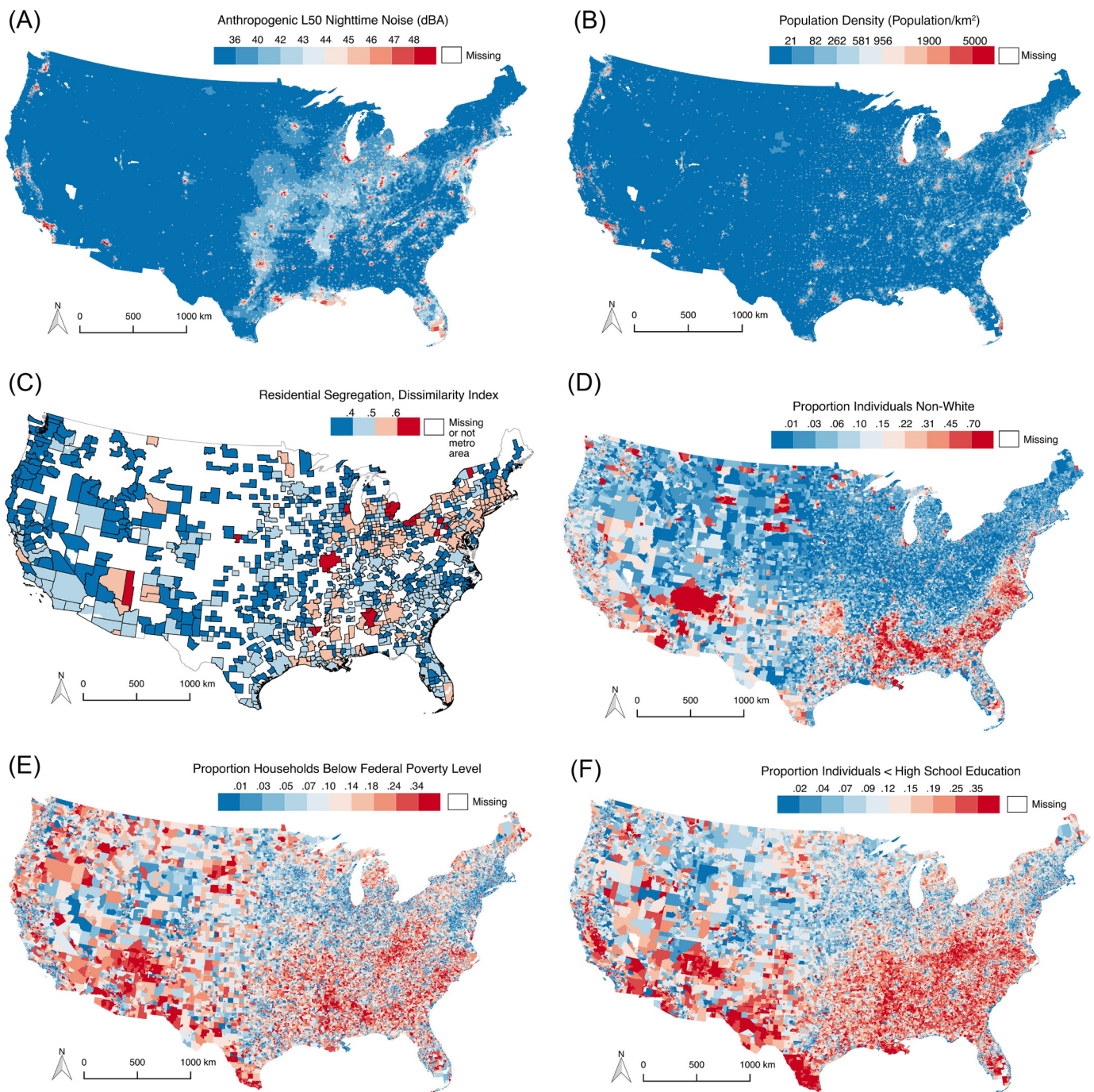


Figure 1. Spatial distribution of (A) anthropogenic L₅₀ nighttime noise; (B) population density; (C) racial residential segregation (urban CBSAs only); (D) non-Hispanic, nonwhite race/ethnicity; (E) poverty; and (F) <high school education (deciles) at the block group-level in the contiguous United States estimated from 2006–2010 American Community Survey data; 2010 shapefiles used to generate these maps downloaded from the NHGIS site: <http://www.nhgis.org>.

improvement in model fit was no longer significant at $\alpha=0.05$. This procedure was completed separately for urban/rural and for L₅₀ nighttime/L₁₀ and daytime/L₅₀ daytime models. In the results section, we refer to an association as nonlinear and statistically significant when likelihood ratio testing indicated that the final model with polynomial terms was a significantly better fit at the $\alpha=0.05$ level than the model without the predictor. When the final model only included a first-degree predictor, we refer to it as a linear association; statistical significance (at the $\alpha=0.05$ level) was determined using a *t*-test. We present results as scatterplots of fitted values with locally weighted smoothing functions (LOESS lines) to

aid in interpretability. We did not predict noise exposure at specific values of the independent variables because predicting at specified populations and population densities would ignore model-derived weights applied to each census block to account for spatial correlations. Instead, we report median and interquartile ranges to summarize the distribution of predicted values for each noise metric according to block group race/ethnicity and socioeconomic characteristics.

In order to calculate \mathbf{W} , the spatial weight matrix, in the main analysis, we defined queen-based neighbors (i.e., only block groups that share a common border or a single common point were considered neighbors) and *S*-coding scheme weights (i.e.,

Table 1. Distribution of anthropogenic L₅₀ nighttime, L₅₀ daytime, and L₁₀ daytime noise among urban residents by race/ethnicity and socioeconomic characteristics at the block group level from the 2006–2010 American Community Survey.

Characteristic	Total, n (%)	Median (IQR) anthropogenic noise, dBA ^a		
		L ₅₀ nighttime	L ₅₀ daytime	L ₁₀ daytime
Total population	254,328,850 (100)	44.3 (42.1–46.5)	48.0 (45.1–50.3)	52.9 (50.7–55.0)
Population <5 y	17,112,446 (6.7)	44.5 (42.3–46.7)	48.1 (45.4–50.5)	53.0 (50.9–55.0)
Population ≥5 y	237,216,404 (93.3)	44.3 (42.1–46.5)	48.0 (45.0–50.3)	52.9 (50.7–55.0)
Race/ethnicity ^b				
Hispanic	44,095,827 (17.3)	45.6 (43.3–47.5)	49.5 (47.5–52.3)	54.1 (52.3–56.0)
Non-Hispanic				
American Indian	1,209,132 (0.5)	42.9 (37.9–45.7)	46.1 (37.8–49.7)	51.5 (44.8–54.4)
Asian	13,081,414 (5.1)	45.4 (43.9–47.1)	49.1 (47.4–51.1)	54.0 (52.4–55.7)
Black	32,935,749 (13.0)	45.6 (43.8–47.6)	49.7 (47.6–52.6)	54.2 (52.4–56.3)
White	157,730,767 (62.0)	43.6 (41.3–45.7)	47.1 (43.3–49.2)	52.3 (49.6–54.2)
Income ≤poverty threshold	33,194,588 (13.3)	45.2 (42.8–47.5)	49.2 (46.6–52.2)	54.0 (51.7–56.1)
Income >poverty threshold ^c	216,181,346 (86.7)	44.2 (42.0–46.3)	47.9 (44.9–50.0)	52.8 (50.6–54.8)
CBSA-level segregation				
0.14 ≤ D _m < 0.40	42,124,233 (16.6)	42.9 (39.2–45.2)	46.7 (41.5–49.4)	51.9 (48.0–54.3)
0.40 ≤ D _m < 0.70	212,204,617 (83.4)	44.5 (42.5–46.7)	48.2 (45.7–50.5)	53.1 (51.1–55.1)
Total population ≥25 y	35,298,009 (100)	44.6 (42.4–46.8)	48.5 (45.7–50.9)	53.3 (51.2–55.4)
<High school education	5,837,943 (16.5)	45.4 (43.0–47.6)	49.4 (46.7–52.3)	54.1 (51.8–56.1)
≥High school education	29,460,066 (83.5)	44.4 (42.3–46.6)	48.3 (45.6–50.7)	53.2 (51.1–55.3)
Total households	95,455,047 (100)	44.3 (42.2–46.5)	48.1 (45.2–50.4)	52.0 (50.9–55.1)
Median household income (USD)				
Quartile 1 (\$2,868–\$39,229)	23,863,693 (25.0)	45.6 (43.2–47.7)	49.8 (47.3–52.8)	54.5 (52.4–56.5)
Quartiles 2–4 (\$39,230–\$249,896)	71,591,354 (75.0)	44.0 (41.8–46.0)	47.6 (44.5–49.6)	52.6 (50.4–54.5)
Linguistically isolated households	5,140,332 (5.4)	45.9 (43.9–47.9)	50.4 (48.2–53.3)	54.8 (53.0–56.8)
Nonlinguistically isolated households	90,314,715 (94.6)	44.2 (42.1–46.4)	48.0 (45.0–50.2)	52.9 (50.7–54.9)
Housing tenure				
Renter-occupied homes	32,996,266 (34.6)	45.3 (43.3–47.4)	49.5 (47.2–52.3)	54.2 (52.3–56.3)
Owner-occupied homes	62,458,781 (65.4)	43.8 (41.6–45.9)	47.4 (43.9–49.4)	52.5 (50.0–54.3)
Total families	63,521,803	44.1 (41.9–46.3)	47.7 (44.6–49.9)	52.7 (50.4–54.7)
Unemployed families	3,343,134 (5.3)	44.5 (42.3–46.8)	48.2 (45.4–50.6)	53.1 (51.0–55.2)
Employed families	60,180,669 (94.7)	44.1 (41.9–46.2)	47.7 (44.5–49.9)	52.7 (50.4–54.7)

Note: CBSA, Core Based Statistical Area; dBA, A-weighted decibels; IQR, interquartile range.

^aPopulation-weighted by block group population (population <5 y, and race/ethnicity), by number of families (unemployment), by households (household income and linguistic isolation, and renters/owners), by population for whom poverty status was determined (poverty), and by population ≥25 y (<high school education).

^bRace/ethnicity does not sum to total; 5,275,961 individuals were of mixed or other race/ethnicity.

^c4,952,916 people did not have poverty status determined and thus are not included in the poverty summary.

variance-stabilizing weights) (Bivand et al. 2008; Tiefelsdorf et al. 1999). Because the choice of neighbors and weights can influence model fit and coefficient estimates, we performed several sensitivity analyses. First, we used distance-based neighbors, where block groups within 5 km of a block group centroid were classified as neighbors. Second, we applied a *W*-coding scheme for weights (i.e., row-standardized). Third, we combined the first two sensitivity analyses.

In additional sensitivity analyses, we simultaneously adjusted models for poverty, education, and housing tenure to assess whether these three dimensions of neighborhood socioeconomic context were confounders. All statistical analysis was performed in R (version 3.2.3; R Development Core Team) using Amazon Web Services and mapping was conducted in QGIS (version 2.12.0; QGIS, <http://qgis.osgeo.org>).

Results

The analysis spanned the contiguous United States and included 933 CBSAs and 214,105 block groups—175,373 urban and 38,732 suburban/rural—after excluding 2,226 block groups missing census or noise variables (Figure 1). The urban block groups contained 257,192,214 individuals, and the rural block groups 45,999,315 individuals. There was a concentration of poverty, nonwhite individuals, and low educational attainment in the South and Southwest. Urban block groups, compared to suburban/rural areas, had, on average, more racial/ethnic minorities (38.0% vs. 19.3%), more renter-occupied homes (34.6% vs. 26.9%), and slightly lower levels of poverty (13.3% vs. 16.8%) [Table 1 (urban) and Table S2 (suburban/rural)]. We observed

moderate correlations (Spearman's $\rho = 0.2\text{--}0.4$) between many of the independent variables, for example, $\rho = 0.20, 0.25,$ and -0.43 between proportion in poverty and proportions unemployed, linguistically isolated, and of white race, respectively, in urban areas (see Figure S1). Individuals, households, and families in urban areas with lower SES had, on average, higher nighttime and daytime noise (Table 1). For example, in urban areas, the median L₁₀ daytime noise estimated for households in the lowest quartile of median income ($\leq \$39,224$) was 54.5 dBA [interquartile range (IQR): 52.4–56.5 dBA] compared to 52.6 dBA (IQR: 50.4–54.5) estimated for households with median income $> \$39,224$. Racial residential segregation was common; 83.4% of the urban study population resided in segregated CBSAs ($D_m > 0.4$) (Table 1), with the most segregated regions in the Northeast and Midwest (Figure 1). Individuals living in more segregated CBSAs, compared to those living in CBSAs with $D_m \leq 0.4$, had higher L₅₀ nighttime [median = 44.5 dBA (IQR: 42.5–46.7 dBA) vs. 42.9 (IQR: 39.2–45.2 dBA)] and L₅₀ daytime [median = 48.2 dBA (IQR: 45.7–50.5 dBA) vs. 46.7 dBA (IQR: 41.5–49.4 dBA)] noise levels (Table 1).

Median population-weighted anthropogenic L₅₀ nighttime, L₅₀ daytime, and L₁₀ daytime noise levels in urban block groups were 44.3 dBA (IQR: 42.1–46.5 dBA), 48.0 dBA (IQR: 45.1–50.3 dBA), and 52.9 dBA (IQR: 50.7–55.0 dBA) (Table 1) compared to 38.8 dBA (IQR: 33.7–42.2 dBA), 37.0 dBA (IQR: 32.8–43.2 dBA), and 43.7 dBA (IQR: 40.2–49.6) in suburban/rural block groups (Table S1), respectively. While the noise metrics differed in magnitude, the spatial distribution was similar with noise levels highest in major metropolitan areas and

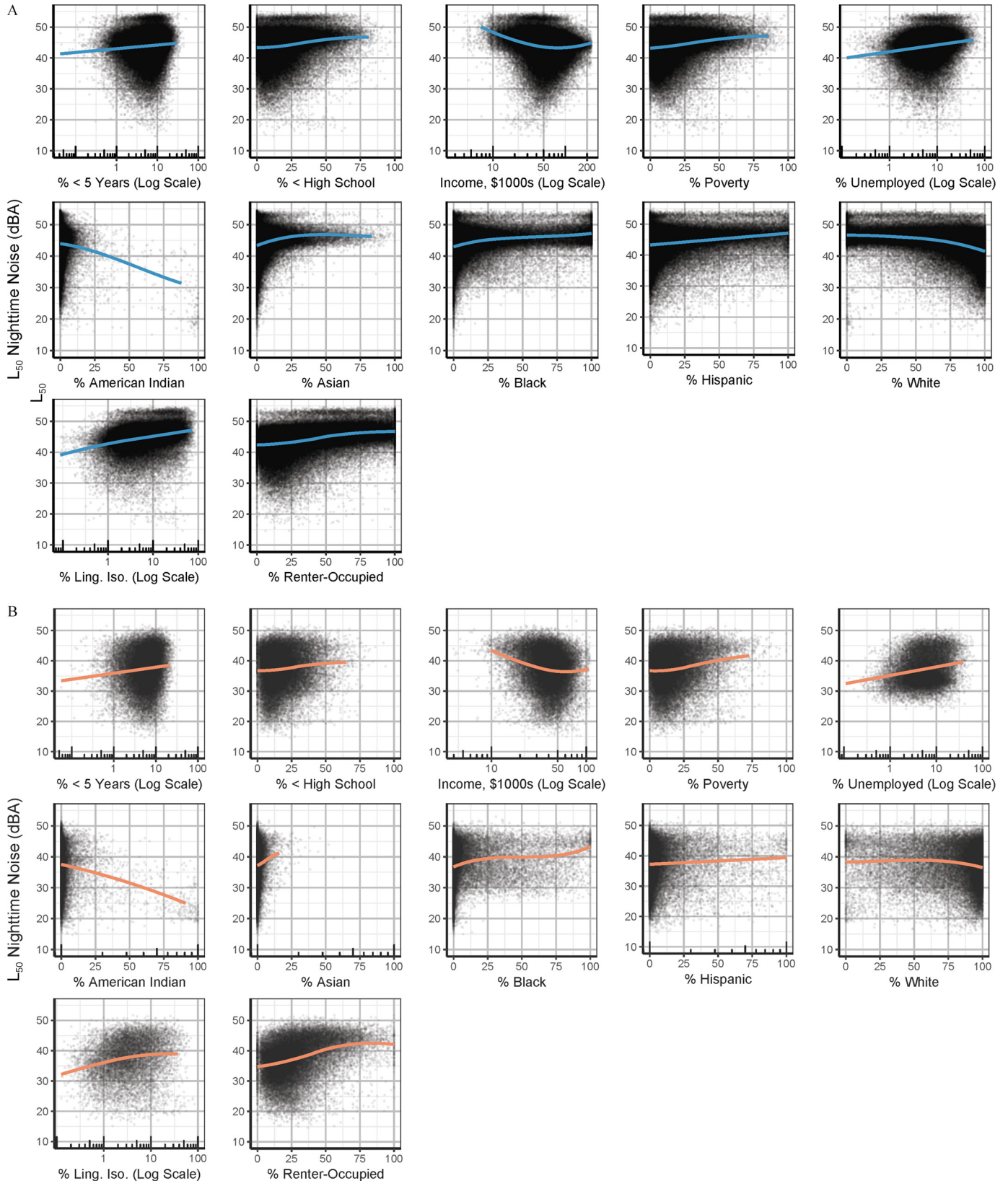


Figure 2. Race/ethnicity and socioeconomic characteristics and anthropogenic L_{50} nighttime noise in (A) urban block groups ($n = 175,373$); and (B) suburban/rural block groups ($n = 38,732$). The figure displays the fitted values (points) showing the relationship between noise and each of 12 demographic characteristics adjusted for block group population and population density and using a queen neighbor definition and variance-stabilizing weights. Four of the plots [% < 5 y, median household income (in thousands), % unemployed, and % linguistically isolated) use a log scale x-axis as noted on the figure. The LOESS line was only estimated when there were >100 observations.

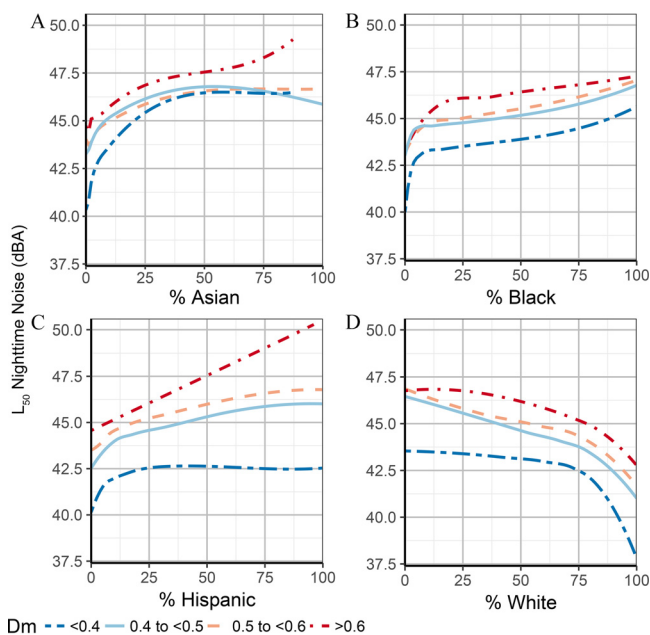


Figure 3. Race/ethnicity and anthropogenic L_{50} nighttime noise in urban block groups ($n = 175,373$), stratified by multigroup racial/ethnic segregation (D_m) for (A) Asians; (B) blacks; (C) Hispanics; and (D) whites. American Indians were excluded due to small numbers in urban areas. The figure displays the LOESS line of the fitted values from 16 (i.e., four categories of segregation and four race/ethnicities) separate spatial error models adjusted for block group population and population density and using a queen neighbor definition and variance-stabilizing weights. The LOESS line was only estimated when there were >100 observations.

lowest in the western United States (Figure 1, Figure S2). Overall, estimated noise levels were highest for Asians, blacks, Hispanics, and those of lower SES (Table 1, Table S2).

Figure 2 presents the results from adjusted spatial error models of the association between our 12 racial/ethnic and sociodemographic variables and nighttime L_{50} noise in urban and suburban/rural block groups. Daytime L_{50} and L_{10} results are available in Figures S3 and S4. Patterns of associations between each predictor and each noise metric were generally consistent in both urban and rural census blocks; as the proportion of nonwhite and low-SES individuals, families, and households increased, estimated nighttime and daytime noise increased. Table S4 summarizes the polynomial terms used for predictors in spatial error models.

We observed significant associations between increased proportions of Asian, black, and Hispanic individuals and higher levels of noise in urban and suburban/rural areas, with the exception of Hispanic ethnicity in rural areas, which was not associated with noise. In urban block groups that contained 75% black residents, the median (interquartile range) nighttime noise level was 46.3 dBA (IQR: 44.3–47.8), while in block groups with 0% black residents, the level was 42.3 dBA (IQR: 40.4–45.5) (Table S3). Conversely, in urban block groups that contained 75% white, the median noise level was 44.8 dBA (IQR: 43.0–46.5), which rose to 47.0 dBA (IQR: 45.4–48.7) in block groups with 0% white residents. For race/ethnicity, the models with best fit all included polynomial terms (Table S4), except for Hispanic race/ethnicity, where we estimated a linear association between nighttime noise in both urban and suburban/rural block groups. Estimated urban nighttime noise increased from 43.7 dBA (IQR: 40.1–45.9) in block groups with 0% Hispanics to 46.5 dBA (IQR: 43.7–48.3) within block groups with 75% Hispanics (Table S3). For American Indian populations, we generally observed reduced

noise as the percent of American Indians increased. Particularly for nighttime noise, the best model fit suggested shape of the association was fairly flat until 7–8% of the population was American Indian, and then there were more rapid reductions in noise levels. In contrast, the best model fit suggested a steeper slope (i.e., more rapid increases in estimated noise) for Asian and black populations at the lower tail of the distribution. For example, nighttime noise was estimated to be about 1.3 dBA higher in block groups containing 0% compared to 10% black individuals, but only 0.2 dBA higher in block groups containing 50% compared to 60% black individuals.

Block groups with higher proportions of individuals with less than a high school education, living in poverty, linguistically isolated, renting, and with a higher proportion of children <5 y were generally associated with higher nighttime and daytime noise levels (Figure 2, Figure S3–S4). For example, urban block groups with 50% of residents in poverty had nighttime noise levels, on average, 3 dBA higher than block groups with 0% (Table S3). The highest levels of noise were estimated in the block groups with the lowest median income; from there, noise levels declined until the median income, where noise levels plateaued.

Figure 3 shows the associations between race/ethnicity and L_{50} nighttime noise across segregation categories (see Table S5 for summary of polynomial terms). Three patterns emerged: first, that across all CBSAs and race/ethnicities, increasing segregation was associated with increased nighttime noise; second, that across all levels of CBSA-level segregation, block groups with higher proportions of Asian, Hispanic, and black residents generally had higher levels of exposure to nighttime L_{50} noise than those with higher proportions of white residents; and third, that the estimated curve shapes (i.e., the LOESS line of the fitted values) remained similar across levels of segregation, with the exception of Hispanics in the least segregated CBSAs, where there was no estimated increase in nighttime noise as the proportion of Hispanics increased above 25%. Results for L_{50} and L_{10} daytime noise were similar (Figures S6 and S7), but differences were less pronounced by level of segregation.

Simultaneous adjustment for poverty, education, and housing tenure in our main analysis had little effect on race/ethnicity and SES estimates in suburban/rural block groups, except for <5 y and education, which, after adjustment, were no longer statistically significant (data not shown). In urban block groups, after adjustment for poverty, education, and housing tenure, the associations for <5 y, Hispanic race/ethnicity, education, and unemployment became nonsignificant (data not shown).

In the primary analysis, we defined queen neighbors and used variance-stabilizing weights. We also conducted sensitivity analyses using three additional neighbor/weight combinations (i.e., queen/ W -coding, distance/ S -coding, and distance/ W -coding). Estimated associations were similar for all neighbor/weight combinations across both urban and suburban/rural block groups (Figure S5).

Discussion

Our findings suggest inequality in the spatial distribution of noise pollution along racial/ethnic and socioeconomic lines across the contiguous United States. Multiple indicators of neighborhood socioeconomic context were associated with increased night and daytime noise, including poverty, unemployment, linguistic isolation, and a high proportion of renters and those not completing high school. Block groups with higher proportions of Asians, blacks, and Hispanics had higher levels of noise, but relationships were rarely linear. The magnitude of these differences may be relevant for health outcomes (Basner et al. 2014); for example, we estimated that census block groups containing 25% black

residents were exposed to a median 3.0 dBA higher nighttime noise than those with 0% black residents. In general, for all race/ethnicity groups evaluated, estimated noise exposures were higher for CBSAs with higher levels of racial segregation. However, disparities persisted between block groups with relatively high proportions of white (>50%) compared to relatively low proportions, except for block groups with high proportions of Hispanics in the least segregated CBSAs. As an example, the median nighttime noise level in block groups containing 75% of each race/ethnicity in the most segregated CBSAs were estimated to be 48.9 dBA, 46.9 dBA, 47.0 dBA, and 45.3 dBA for Asian, black, Hispanic, and white race/ethnicity, respectively.

Early indications of inequality in noise pollution in the United States came from the U.S. EPA in the 1970s. Survey respondents of higher SES tended to live in quieter neighborhoods and reported hearing fewer airplanes, traffic, and people's voices, but more motorcycles, garden power tools, and sports cars (U.S. EPA 1977). More recently, in nearly 2000 block groups in the Twin Cities in Minnesota, Nega et al. (2013) modeled 24-h average traffic noise using data on roadways, traffic volume, building height, airplane flight paths, and other information. They reported significantly increased traffic noise as block group median household income and housing value fell and the proportion of non-white residents and persons aged >18 y increased, results from a spatial error model that simultaneously adjusted for all four independent variables. Nega et al. (2013) joined a handful of others to account for spatial dependence in their models when assessing inequality in noise pollution, with heterogeneous results (Bocquier et al. 2013; Carrier et al. 2016; Havard et al. 2011). Carrier et al. (2016) modeled mean 24-h traffic noise levels in 7,456 city blocks in Montreal, Canada, and used spatial error models to estimate associations with race/ethnicity and SES at the city block level. Like us, they observed increasing noise levels with an increasing proportion of low-income and nonwhite individuals. In Marseilles, France, Bocquier et al. (2013) reported that census blocks of intermediate SES (defined by a deprivation index constructed from 17 variables) had the highest modeled noise levels. In Paris, France, Havard et al. (2011) found an inverse relationship where modeled noise levels were higher in a 250-m buffer surrounding the residences of individuals with more education and higher valued homes. Desire of individuals to live near transportation networks may explain the inverse relationship. Indeed, among nearly 2 million individuals in Rome, Cesaroni et al. (2010) found that higher area SES and individual education were associated with increased traffic in a 150-m buffer around participants' homes, except in the city center, where traffic density was highest, and less affluent neighborhoods and individuals were closer to roads. We observed indications of the same phenomenon; the relationship between median household income and noise was U-shaped in both urban and rural areas.

There is a broad literature concerning variation in air pollution in relation to social factors (Bell and Ebisu 2012; Hajat et al. 2015; Miranda et al. 2011). Our results are consistent with and may partially overlap this literature, due to co-occurrence of noise and air pollution. However, despite co-occurrence, noise and air pollution have only been moderately correlated (Spearman's correlation coefficients 0.3–0.6) in New York City, London, and Vancouver (Davies et al. 2009; Fecht et al. 2016; Ross et al. 2011), and correlations did not differ by deprivation in London (Fecht et al. 2016). Furthermore, epidemiologic studies have reported associations between noise and multiple health outcomes after adjusting for air pollution, including associations with cognition and behavioral problems in children (Clark et al. 2012;

Hjortebjerg et al. 2016), birth weight (Gehring et al. 2014), cardiovascular mortality (Gan et al. 2012), and diabetes (Sørensen et al. 2013).

To our knowledge, no prior studies have reported a positive association between noise levels and a community-level measure of social inequality, in this case, racial segregation. This observation is consistent with Boyce's power-weighted decision theory (Boyce 1994) that social inequalities are associated with the distribution of environmental pollution, perhaps due to political power imbalances between the wealthy and the poor. It is also consistent with recent U.S. literature reporting positive associations between modeled air pollution and community segregation (Bravo et al. 2016; Jones et al. 2014; Rice et al. 2014). In the case of environmental noise, spatial segmentation of neighborhoods, workplaces, and basic service locations due to CBSA-level racial segregation may increase vehicle miles traveled (Morello-Frosch and Jesdale 2006), which could, in turn, contribute to noise pollution. This situation could create a feedback loop in which worse noise pollution catalyzes segregation (Bjørnskau 2005).

Our study suggests racial disparities in noise exposure, and noise has previously been linked to a number of negative health outcomes, including hypertension and sleep difficulties (Haralabidis et al. 2008; Münzel et al. 2014; Muzet 2007). Future work is needed to estimate how much differences in noise exposure may explain racial disparities in noise-related health outcomes. Disadvantaged populations may also have increased susceptibility to noise. For example, a recent German study reported that among 3,300 participants free from depressive symptoms at baseline, annual average noise exposure >55 dBA was associated with depressive symptoms at the 5-y follow-up, but only among those with <13 y of education (Orban et al. 2016). Worse quality housing, increased exposure to indoor noise, and comorbid conditions may help explain this disparity (Evans and Marcynyszyn 2004). Wealthier individuals may have greater ability to invest in noise abatement technologies (e.g., triple-pane windows, air-conditioning), and thus may have lower actual exposures to noise than less affluent individuals living in census blocks with the same estimated level of noise exposure. While living near urban centers may provide benefits like access to public transit and cultural assets, in some cities, the accompanying road and rail traffic may also increase the level of outdoor noise (Fyhri and Klæboe 2006).

For the past 40 y, many noise studies have relied on a simple relationship between population density and community noise exposure to estimate ambient noise in the absence of *in situ* measurements (Schomer et al. 2011). In addition to population density, our geospatial sound model incorporated multiple explanatory variables describing the type and intensity of human activity, but did not include demographic descriptors. Unfortunately, we were only able to assess the distribution of noise at the block group level in this cross-sectional study. We could not identify the processes and procedures—for example, regulatory policies, neighborhood economic sorting, or land use decisions—that might explain inequality in noise levels, nor could we explain why some groups appeared more exposed to noise than others. We were unable to examine individual modifying characteristics, such as housing quality, work environment and location, prevalent illness, or propensity to noise sensitivity (Stansfeld and Shipley 2015). Additionally, our noise model did not differentiate between various anthropogenic sources of sound, which may have differential health effects (Basner et al. 2011). Although the noise model performed well ($R^2 \geq 0.8$), our prediction of outdoor noise is likely to contain measurement error (Mennitt and Frstrup 2016). Finally, our analysis

did not include L_{eq} estimates (i.e., a measure of equivalent continuous sound often used for noise standards). Therefore, we are unable to make comparisons to established WHO or U.S. EPA noise guidelines or to the majority of epidemiologic studies (Basner et al. 2014).

Despite these limitations, our study made several contributions. We characterized noise pollution across the contiguous United States for the first time since the early 1980s. The use of polynomial terms in this large sample allowed us to characterize nonlinear associations without assuming a constant slope over all values of each predictor. We accounted for spatial autocorrelation and implemented a spatial error model to avoid violating modeling assumptions. We defined neighbors and weights in multiple ways, given prior evidence that changing these definitions can impact inference (Bivand et al. 2008). Our sensitivity analyses demonstrated the stability of our results. Regardless of neighbor/weight definitions, we estimated similar relationships between race/ethnicity, SES, and noise almost universally, with the highest estimated noise levels in block groups with higher percentages of minorities and lower SES individuals.

Conclusion

Our analysis of estimated outdoor noise exposures in census block groups throughout the contiguous United States found evidence of higher noise exposures in census block groups characterized by lower SES and higher proportions of American Indian, Asian, black, and Hispanic residents. These associations were stronger in more racially segregated communities. Differences in noise exposure may have implications for more fully understanding drivers of environmental health disparities in the United States.

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