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Sociodemographic Patterns of Exposure to Civil Aircraft Noise in the United States

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Background: Communities with lower socioeconomic status and higher prevalence of racial/ethnic minority populations are often more exposed to environmental pollutants. Although studies have shown associations between aircraft noise and property values and various health outcomes, little is known about how aircraft noise exposures are sociodemographically patterned.

Objective: Our aim was to describe characteristics of populations exposed to aviation noise by race/ethnicity, education, and income in the United States.

Methods: Aircraft noise contours characterized as day–night average sound level (DNL) were developed for 90 U.S. airports in 2010 for DNL ≥ 45 dB(A) in 1-dB(A) increments. We compared characteristics of exposed U.S. Census block groups at three thresholds (≥ 45, ≥ 55, and ≥ 65 dB(A)), assigned on the basis of the block group land area being $\geq 50\%$ within the threshold, vs. unexposed block groups near study airports. Comparisons were made across block group race/ethnicity, education, and income categories within the study areas ($n = 4{,}031$–$74{,}253$). We performed both multinomial and other various multivariable regression approaches, including models controlling for airport and models with random intercepts specifying within-airport effects and adjusting for airport-level means.

Results: Aggregated across multiple airports, block groups with a higher Hispanic population had higher odds of being exposed to aircraft noise. For example, the multinomial analysis showed that a 10-percentage point increase in a block group's Hispanic population was associated with an increased odds ratio of 39% (95% CI: 25%, 54%) of being exposed to ≥ 65 dB(A) compared with block groups exposed to <45 dB(A). Block groups with higher proportions of residents with only a high school education had higher odds of being exposed to aircraft noise. Results were robust across multiple regression approaches; however, there was substantial heterogeneity across airports.

Discussion: These results suggest that across U.S. airports, there is indication of sociodemographic disparities in noise exposures. https://doi.org/10.1289/EHP9307

Introduction

Communities with low socioeconomic status (SES) and high prevalence of racial/ethnic minority populations are often exposed to greater numbers and concentrations of environmental hazards (Mohai et al. 2009; Zwickl et al. 2014). In the United States, disproportionate exposure may reflect procedural injustices in environmental regulations, institutional and individual discrimination, and racist housing policies manifesting in residential segregation and suburbanization, as well as structural factors such as politics and economics that affect facility siting and the racialization of labor markets (McCartney et al. 2019; Morello-Frosch 2002).

One exposure for which disproportionate burdens may be felt is aircraft noise due to a complex set of factors including land-use patterns connected with airport economies and flight paths. Aircraft noise is a major source of annoyance and complaints in communities surrounding airports (Miller et al. 2021). In addition, studies have related aircraft noise to sleep disturbance, impairments in children's cognition, negative birth outcomes, and cardiovascular disease outcomes, as well as risk factors such as hypertension (reviewed by Basner et al. 2017). An important first step to understanding potential health impacts in the United States is to investigate aircraft noise exposure patterning related to community sociodemographic characteristics.

A popular method for investigating population impacts of aircraft noise is to evaluate its association with property values (e.g., Nelson 2004); however, most of these analyses do not directly evaluate the distribution of noise exposures as a function of a community's sociodemographic characteristics. A few studies have specifically investigated the distribution of sociodemographic characteristics around airports but, to our knowledge, only around individual airports. Ogneva-Himmelberger and Cooperman (2010) found a greater prevalence of racial/ethnic minority and lower-income populations within areas with aircraft noise levels >55 dB(A) compared with unexposed areas within a 21-km radius surrounding Boston's Logan International Airport. Similarly, Sobotta et al. (2007) reported that the primary predictor of aviation noise around a commercial airport in Arizona was race/ethnicity, followed by poverty. Most et al. (2004) investigated patterns around St. Louis-Lambert Field and found a higher prevalence of racial/ethnic minority and lower SES populations living in areas of high noise levels [60–65 dB(A)]; however, they found a lower prevalence of racial/ethnic minority and higher SES populations in areas with even more highly elevated noise levels [70–75 dB(A)]. A UK study in Birmingham (Brainard et al. 2004) found "only rather weak evidence" of an association between combined transportation (i.e., road, rail, and airport) noise exposure and ethnicity and socioeconomic deprivation. Alternatively, a study in the Netherlands looking at transportation noise exposures separately found different relationships by

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noise exposure source, most relatedly, lower social inequality associated with aircraft noise exposure (Kruize et al. 2007; WHO Regional Office for Europe 2010). Dreger et al. (2019) performed a systematic review of studies of environmental noise exposure in the World Health Organization (WHO) European Region and found mixed results in the eight studies they evaluated but an indication of higher noise exposure in groups of lower socioeconomic position; they proposed that mixed results could be due to differences in how noise and social inequality were measured. Although studies of individual airports are valuable, it is unclear what the sociodemographic patterns of aircraft noise exposure would be across and between multiple airports evaluated using the same noise and sociodemographic measures.

Our objective was to investigate whether racial/ethnic minority and low-SES populations in the United States are disproportionately exposed to aircraft noise. To this end, we used spatially resolved noise measures modeled using the method required for environmental impact assessment and compliance for 90 U.S. airports spanning all regions and various hub types. We paired these data with U.S. Census and American Community Survey (ACS) data to perform an investigation of the sociodemographic distributions around U.S. airports. We also estimated associations with sociodemographic characteristics controlling for distance to airport and evaluated between- and within-airport relationships.

Methods

Study Airports

Ninety airports with available noise modeling inputs were provided by the Federal Aviation Administration (FAA) for this study. These airports comprised several hub types, categorized on the basis of percentage passenger enplanement (49 U.S. Code § 47102), including 29 large, 27 medium, 29 small, and 5 nonhub airports located in 40 of the 50 states (Figure 1). For 2010, total passenger enplanements from these 90 airports represented 87% of all passenger enplanements at U.S. airports (FAA n.d.). The majority of the airports were located in urban/metropolitan areas—only eight airports (9%) had a study area that included at least one rural census tract as defined by the U.S. Department of Agriculture's rural–urban commuting area (USDA 2019).

Noise and Population Data

Annual average noise levels from aircraft were estimated around each of the 90 study airports for the decennial census year 2010. For each period, both day–night average sound level [DNL; sound ≥45 dB(A)] and nighttime average sound level (LAeqN; sound ≥45 dB(A)) were modeled in 1-dB(A) increments. DNL is calculated as a 24-h annualized average noise level, based on an entire year of operations modeled to a single average annual day, with a 10-dB(A) penalty for nighttime noise (noise from 2200 to 0700 hours). The U.S. Department of Transportation's John A. Volpe National Transportation Systems Center (Volpe) conducted the noise computations using the FAA's Aviation Environmental Design Tool (AEDT; version 2d) from ground-track statistics. The source of aircraft operations data was the Enhanced Traffic Management System, which provided operations under Instrument Flight Rules for the observed year, including the length of the mission (or stage length), time of the operation, as well as the International Civil Aviation Organization aircraft type, excluding helicopter operations. Operations were annualized using the following groupings: Aircraft Noise and Performance aircraft type, day- or nighttime, operation airport, and stage length. Volpe used the dynamic grid capabilities to automatically determine the grid size.

Population data at the 2010 U.S. Census block group level were acquired from the ACS (5-y estimates from 2008–2012) (U.S. Census Bureau n.d.-a). A block group is the smallest statistical unit for which the U.S. Census reports data; it is a cluster of blocks within a census tract (a relatively permanent statistical subdivision of U.S. counties) and can contain 600–3,000 people (240–1,200 housing units) (U.S. Census Bureau n.d.-c). This study accesses only public-use data from the U.S. Census/ACS, which thus does not include individually identifiable data and is not considered human subjects research.

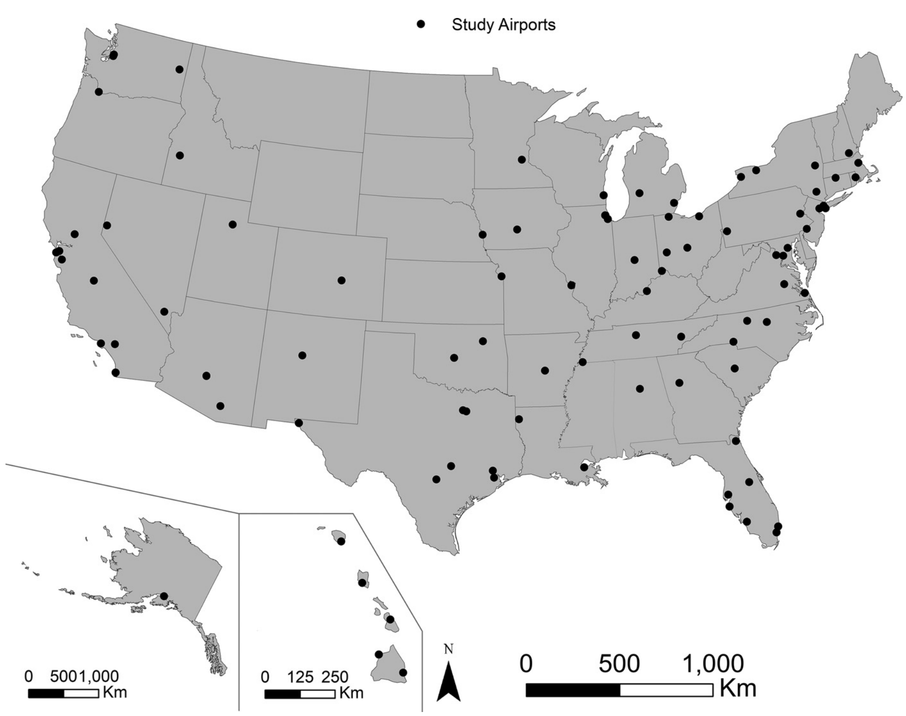

Figure 1. Map of 90 study airports (represented as points in the figure) across the United States. Figure designed with ArcMap 10.6.

We generated data tables on race/ethnicity, education, and SES using raw data and SAS (SAS Institute Inc.) code downloaded from the ACS website (U.S. Census Bureau n.d.-d). Race/ethnicity is collected in the census by self-identification from categories based on social definitions recognized in the United States (U.S. Census Bureau n.d.-b). We calculated the percentage of each of the following characteristics for each block group population: *a*) race/ethnicity: non-Hispanic white, non-Hispanic Asian, non-Hispanic black, Hispanic, and other (all other non-Hispanic/non-white races/ethnicities); *b*) education: no high school diploma or General Education Development (GED), high school diploma or GED, and education of at least some college; and *c*) household annual income (in USD): <\$25,000, \$25,000 to <\$50,000, \$50,000 to <\$75,000 and ≥\$75,000. Hereafter, we consider the reference groups to be non-Hispanic whites for race/ethnicity, education of at least some college, and household incomes ≥\$75,000, with the remaining groups considered to be "socially vulnerable groups."

To assess the reliability of the ACS block group data used in the analyses, we calculated the coefficients of variation (CVs) for each of our derived variables used during modeling, for each block group. Following the ACS General Handbook (U.S. Census Bureau 2020), the coefficient of variation (CV) was calculated using Equation 1:

$$CV = \frac{\left(\frac{MOE}{1.645}\right)}{Estimate} \times 100, \qquad (1)$$

where *MOE* is the associated margin of error for the estimate, and *Estimate* is the derived estimate for the variable of interest within each block group (U.S. Census Bureau 2020). Margins of error accompany each block group estimate value but require additional calculation if ACS estimates are aggregated. For our analysis, we represented block group estimates as percentages relative to the entire block group population; thus, we added the fractional MOEs in quadrature [i.e., the square root of the sum of squares; see Harvard University (n.d.)]. For any derived estimates that were aggregated by summing individual ACS estimates, we added the ACS MOEs in quadrature. Block group CVs were binned into "high," "medium," and "low" data reliability as defined by Esri whereby CVs $\leq 12\%$ are "high," CVs between 12% and 40% are "medium," and CVs $>40\%$ are "low" (Esri 2014).

Exposure Assignment

We grouped noise contours into three categories (i.e., $\geq 45\,\mathrm{dB(A)}$, $\geq 55\,\mathrm{dB(A)}$, and $\geq 65\,\mathrm{dB(A)}$) to coincide with the WHO Regional Office for Europe's recommendation for noise and health (WHO Regional Office for Europe 2018), the European Union Aviation Safety Agency guideline (EASA 2021), and FAA regulations for noise abatement funding (FAA n.d., 2000), respectively. Noise contour data were provided in shapefile format, which we imported into a Geographic Information System (GIS; ESRI ArcMap, version 10.6). These grouped noise contours were overlaid onto 2010 Census block groups using ArcMap (ESRI). Block groups with $\geq 50\%$ of their area inside the noise contour threshold being investigated were assigned as "exposed," and all others were assigned as "unexposed." The unexposed group was limited to block groups within a certain distance from each study airport, termed the "maximum extent." The maximum extent was different for each airport and, similar to as used by Sobotta et al. (2007), was defined as the maximum distance a noise contour threshold reached from the center of the airport (Figure 2). A buffer centered at the airport and

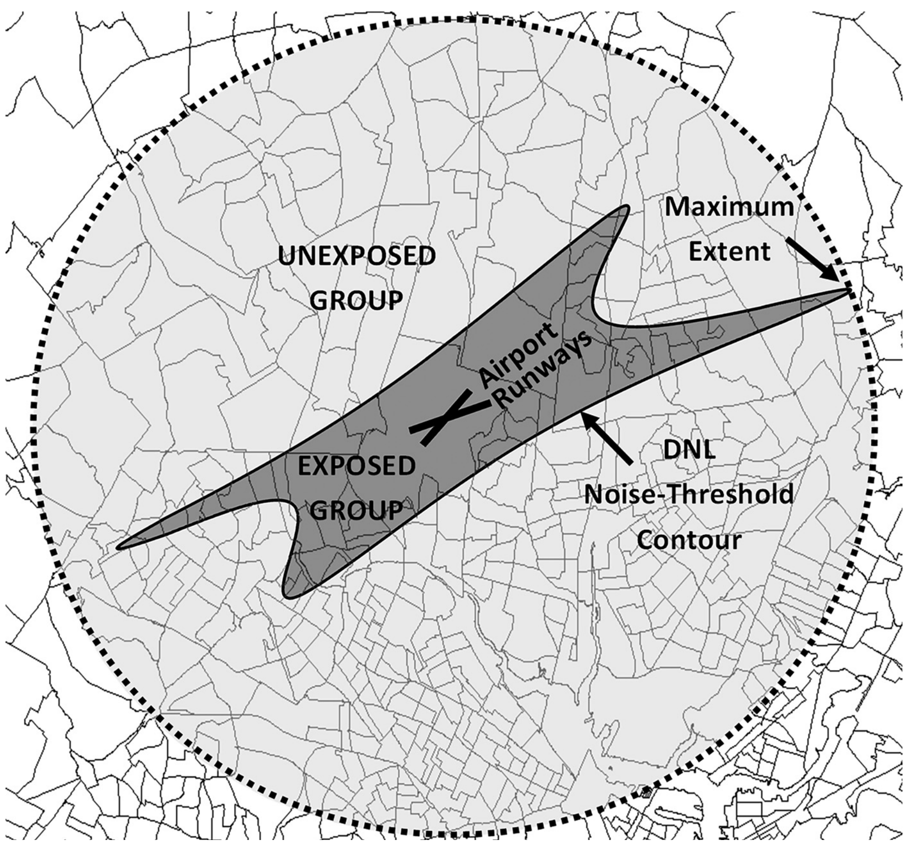

Figure 2. Example of a noise contour threshold around a fictional airport and assignment of exposed and unexposed block groups (i.e., underlying polygons). The maximum extent is defined as the smallest radius of a circle centered on the airport that encompasses the entire noise contour. Block groups with ≥50% of their area within the noise contour are assigned to the exposed group, and block groups not in the exposed group but with ≥50% of their area within the maximum extent are assigned to unexposed group. Block group layer from ArcMap 10.6. Note: DNL, day–night average sound level.

extending out a radius equal to the maximum extent defined the geographic limit of the unexposed comparison group. Block groups along this edge were included as long as ≥50% of their area was within the buffer. Airport-specific maximum extents were calculated for each of the three noise contour thresholds; thus some block groups assigned to the unexposed group for one noise threshold could have been excluded completely for another. Water bodies were removed from the block group GIS layer before any area calculations; however, we kept all other land-use types in the analysis given that our analysis was confined to near-airport areas where we would not expect there to be much land area designated as more unpopulated than water bodies. To test this claim, we overlaid the 2010 national green space layer [parks, gardens, and forests (Esri 2021)] and calculated the additional land area that would be removed from our analyses if green spaces were also excluded—it amounted to <2–4% of the combined 45–65 dB(A) study areas.

To compare across increasingly higher exposure categories (45 to <55, 55 to <65, and ≥65 dB(A)) relative to the base category (<45 dB(A)), we included data from 74,253 block groups surrounding the 90 airports. For comparison at thresholds, we included only airports that had ≥100 block groups identified within the airport group (threshold specific). As the noise threshold increased, the total number of block groups included in the analyses decreased—for the DNL thresholds of 45, 55, and 65 dB(A), analyses included data from 74,170 block groups (86 airports), 32,283 block groups (61 airports), and 4,031 block groups (15 airports), respectively. Because LAeqN contours were generally much smaller than the DNL contours, the number of airports included in the LAeqN analyses were even fewer. For LAeqN thresholds of 45, 55, and 65 dB(A), analyses included data from 54, 10, and 0 airports, respectively (thus, no analyses could be completed for the LAeqN 65-dB(A) contours).

Analytical Methods and Calculations

To understand whether socially vulnerable groups living near U.S. airports were more or less exposed to aircraft noise than socially advantaged groups in the same areas, we compared the percentage of the socially vulnerable group exposed compared with unexposed for each noise threshold using mean-difference plots and various logistic modeling approaches. We displayed the univariable comparisons using mean-difference plots to highlight the variability across airports for the change in percentage for each socially vulnerable grouping exposed as compared with the entire airport group (exposed and unexposed) mean.

We performed both multinomial multivariable regression and multivariable hybrid mixed-effect logistic regression (all airports grouped together for both). Multinomial regression used ordered outcome measures to determine the relationship of sociodemographic characteristics at higher noise level categories (45 to <55, 55 to <65, and ≥65 dB(A)) relative to the base category (<45 dB(A)). Multivariable hybrid mixed-effect logistic regression with a random intercept was used to separate within- and between-cluster (airport) effects (Begg and Parides 2003; Neuhaus and Kalbfleisch 1998; Schunck and Perales 2017), as given by Neuhaus and Kalbfleisch (1998) in Equation 2:

$$logit\, pr(Y_{ij}=1|X_{ij},a_i)=a_i+\beta_B\bar{X}_i+\beta_W(X_{ij}-\bar{X}_i), \qquad (2)$$

where Y_{ij} is the outcome exposure to aircraft noise at three thresholds [≥45, ≥55, and ≥65 dB(A)]; $i=1,2,\ldots,k$ airports; $j=1,2,\ldots,n_i$ block groups within-airport i; a is the distribution of the random effect; and between-airport is denoted as $\bar{X}_i=\sum_{j=1}^{n_i} X_{ij}\div n_i$ and within-airport as $(X_{ij}-\bar{X}_i)$.

Sensitivity analyses using traditional multivariable logistic regression with a categorical airport term (with both DNL and LAeqN contours) and Bayesian multiple logistic regression with a random intercept (with just the DNL contours) were conducted. In addition, we tested if results changed by controlling for distance to the airport, which allowed us to investigate whether the orientation of the noise contours (and flight patterns) led to exposure disparities or not. It may be that being within a certain distance to an airport is seen as a disamenity regardless of actual noise exposure. Airports could bring other disamenities, such as road traffic and associated traffic noise and air pollution. Univariable logistic models were generated for all variables tested (with both DNL and LAeqN contours). All regression modeling was conducted in R (version 3.6.3; R Development Core Team) using the lme4 package. Bayesian regression in R was conducted with the brms and rstan packages, which served as an interface to Stan (version 2.21.2; Stan Development Team).

Results

Table 1 details the characteristics of block groups for the exposure categories: unexposed, 45 to <55, 55 to <65, and ≥65 dB(A). Block groups included in our study had populations that were mostly non-Hispanic white, had at least a high school education (or GED), and had household incomes of ≥$75,000. The calculated CVs for the block groups used in our analysis were categorized as medium and low (Table 2).

Figure 3 shows the mean-difference plots for the DNL 55-dB (A) threshold for all socially vulnerable race/ethnicity, educational

Table 1. Percentage of block group characteristics by exposure group.

	Exposure group			
Variables	<45 dB(A)	45 to <55 dB(A)	55 to <65 dB(A)	≥65 dB(A)
Race/ethnicity (%)				
Non-Hispanic black	16.4	18.6	19.7	25.7
Non-Hispanic Asian	8.1	8.5	9.0	2.7
Hispanic	21.9	26.8	32.3	38.9
Non-Hispanic other	3.1	3.0	2.9	3.1
Non-Hispanic white	50.6	43.1	36.0	29.6
Education (%)				
<High school diploma or GED	14.1	17.0	20.5	23.9
High school diploma or GED	23.5	25.6	27.4	29.3
>High school diploma or GED	62.4	57.4	52.1	46.8
Household income (%)				
<$25,000	22.0	23.9	25.9	26.0
$25,000 to <$50,000	22.3	23.6	24.8	24.9
$50,000 to <$75,000	17.3	17.6	17.8	19.5
≥$75,000	38.5	34.9	31.4	29.6

Note: Educational attainment is based on the block group population ≥25 years of age. GED, General Education Development

Table 2. Percentage of data classified as high, medium, and low reliability based on the coefficients of variation (CV) for all block groups used in analysis.

Variables	High reliability (CV ≤12%)	Medium reliability (12% < CV ≤40%)	Low reliability (CV >40%)	Not available
Race/ethnicity (%)				
Non-Hispanic black	0.1	21.6	55.3	23.0
Non-Hispanic Asian	<0.1	11.4	54.1	34.4
Hispanic	0.2	25.0	61.9	12.9
Non-Hispanic other	<0.1	1.7	65.0	33.3
Non-Hispanic white	2.9	68.8	23.6	4.8
Education (%)				
<High school diploma or GED	<0.1	27.4	65.5	7.0
High school diploma or GED	<0.1	62.0	36.7	1.3
>High school diploma or GED	2.0	87.0	10.6	0.4
Household income (%)				
<$25,000	<0.1%	39.1	56.9	3.9
$25,000 to <$50,000	0.0	42.2	55.7	2.1
$50,000 to <$75,000	0.0	34.0	62.9	3.2
≥$75,000	0.3	61.4	35.1	3.2

Note: CV, coefficient of variation; GED, General Education Development.

attainment, and annual household income groups investigated. The socially vulnerable group with the largest mean of the mean differences between the exposed block groups and the mean of all block groups around the airport were Hispanics. On average, across 61 airports, the exposed groups' percentage Hispanic population was 3.1 [95% confidence interval (CI): 0.9, 5.3] percentage points higher than the mean of all block groups around the airport. The second largest mean of the mean differences was that of the group with only a high school education [2.9 (95% CI: 1.8, 3.9) percentage points higher than the mean of all block groups around the airport]. The mean of the mean differences was found to be above zero for all socially vulnerable groups, except non-Hispanic Asian populations, but there was variability across airports. For the same socially vulnerable group, some airports had positive mean differences (i.e., socially vulnerable groups were more likely to be exposed), whereas others had negative mean differences (i.e., socially vulnerable groups were less likely to be exposed). Both the DNL 45-dB(A) (Figure S1) and DNL 65-dB(A) (Figure S2) thresholds showed similar variability across airports, with the mean of the mean differences >0 for most of the socially vulnerable groups.

In multinomial multivariable analysis, odds ratio (OR) patterns were generally nonmonotonic with increasing exposure levels. Socially vulnerable groups tested had higher odds of being in block groups exposed to noise levels of DNL 45 to <55 dB(A) compared with block groups with DNL <45 dB(A) (Table 3). In addition, the socially vulnerable groups tested had higher odds of being exposed to DNL 55 to <65 and to ≥65 dB(A), respectively, compared with block groups exposed to <45 dB(A) (Table 3), except for the percentage non-Hispanic Asian population, which showed lower odds at DNL ≥65 dB(A). For example, each 10-percentage point increase in a block group's non-Hispanic Asian population was associated with 13% (95 CI: 10%, 17%) increased odds of being exposed to DNL 55 to <65 dB(A) and with 51% (95: 31%, 65%) decreased odds of being exposed to ≥65 dB(A), respectively, compared with block groups exposed to <45 dB(A). The largest odds were for Hispanic populations, where, for example, each 10-percentage point increase in a block group's Hispanic population was associated with 39% (95 CI: 25%, 54%) increased odds of being exposed to ≥65 dB(A) compared with block groups exposed to <45 dB(A). The odds were higher for block groups with a higher percentage of the population having only a high school diploma or GED and with annual household incomes of $25,000 to <$50,000 and $50,000 to <$75,000 than for block groups with a higher percentage of the population having less than a high school diploma or GED or annual household incomes of <$25,000, respectively.

Results from the multivariable hybrid mixed-effect logistic model approach allowed us to determine which sociodemographic predictors were most strongly associated with exposure disparities and to separate within-airport effects from between-airport differences (Table 4). All socially vulnerable groups tested were observed to have higher odds of being exposed to noise levels at the DNL ≥45-dB(A) threshold (Table 4), similar to the multinomial model for populations exposed to noise levels of DNL 45 to <55 dB(A) compared with those exposed to DNL <45 dB(A). Again, the largest odds were for Hispanic populations, where each 10-percentage point increase in a block group's Hispanic population was associated with 13% (95 CI: 11%, 14%) increased odds of being exposed to higher noise. In addition, each 10-percentage point increase in a block group's population with annual household incomes of $25,000 to <$50,000 and $50,000 to <$75,000 were observed to have 6% (95% CI: 4%, 8%) higher odds of being exposed to noise levels at the DNL ≥45-dB(A) threshold.

Regressions using the DNL 55-dB(A) threshold resulted in generally similar trends as the DNL 45 dB(A) threshold, with non-Hispanic Asian and Hispanic populations most highly exposed, along with people with no college (Table 4). The largest odds were for people with only a high school diploma or GED, where each 10-percentage point increase in a block group's population with a high school diploma or GED was associated with 21% increased odds of being exposed to higher noise. Associations with household income were modest, as was the association with percentage non-Hispanic black.

Analyses for the DNL 65-dB(A) threshold yielded ORs with wider CIs, with positive associations remaining for Hispanic, lower education, and lower-income populations (Table 4). We also observed a strong inverse association with the percentage non-Hispanic Asian population, unlike what was seen for the 45- and 55-dB(A) thresholds. For all thresholds, results generally did not change even after controlling for a block group's distance to the airport (Table S1).

Our results were similar to those obtained by using alternative modeling approaches [i.e., traditional multivariable regression (Tables S2–S4) and Bayesian regression (Tables S5–S7)]. Again, results generally did not change even after controlling for a block group's distance to the airport. We also tested the socially vulnerable group terms with LAeqN thresholds of 45 and 55 dB(A) using traditional multivariable logistic approaches (there were no airports with ≥100 block groups available for analysis at the 65-dB(A) threshold). Generally, these contours were smaller but of the same shape as the DNL contours at the same airport. As such, the model results for LAeqN 45 dB(A) (Table S8) were similar to the model

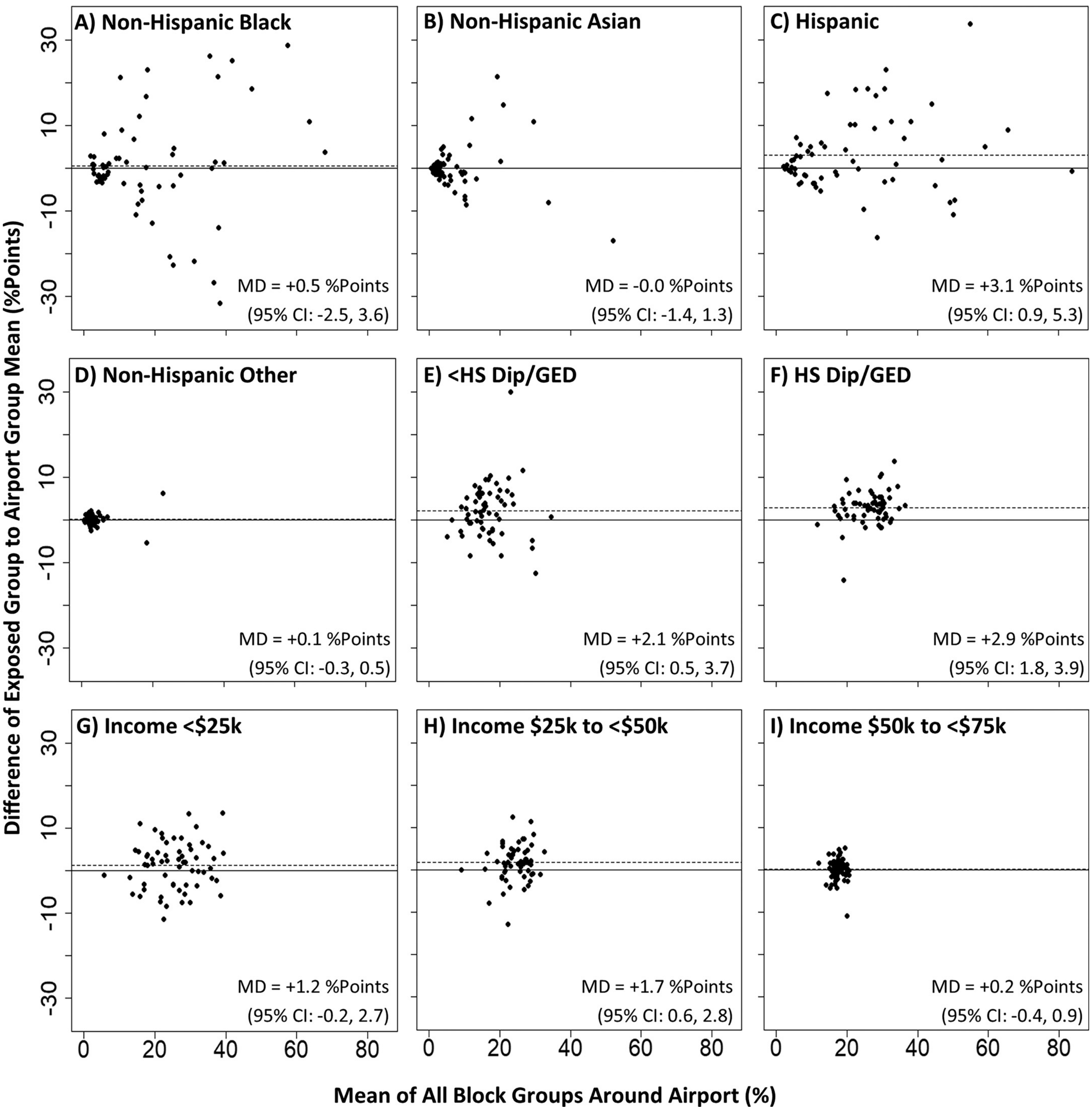

Figure 3. Mean-difference plots for socially vulnerable groups: (A) non-Hispanic black, (B) non-Hispanic Asian, (C) Hispanic, (D) non-Hispanic other, (E) no high school diploma or GED, (F) high school diploma or GED only, (G) annual household income <\$25,000, (H) annual household income \$25,000 to <\$50,000, and (I) annual household income \$50,000 to <\$75,000. In (A–I), each airport-specific relationship is represented by a point ($n_{\text{airport}} = 61$), where the x-axis is the mean of the percentage socially vulnerable group for all block groups within the maximum extent and the y-axis is the mean difference between the percentage exposed for the socially vulnerable group and the airport mean. Airports above the zero line were those found to have block groups with a greater percentage of socially vulnerable groups within the 55-dB(A) noise contour than the mean of all block groups around that airport (i.e., more exposed). Airports below the zero line were those found to have block groups with a lower percentage of socially vulnerable groups within the 55-dB(A) noise contour than the mean of all block groups around that airport (i.e., less exposed). Points along the zero line are airports where there is no difference in percentage socially vulnerable groups within the DNL 55-dB(A) contour (i.e., exposed) relative to the airport mean. Dashed lines represent the mean of the mean differences across all airports. Note: CI, confidence interval; DNL, day–night average sound level; GED, General Education Development; HS dip, high school diploma; k, thousand; MD, mean difference.

results for DNL 55 dB(A), and model results for LAeqN 55 dB(A) (Table S9) were similar to the model results for DNL 65 dB(A). However, there were some modest differences, including slightly stronger associations with education for LAeqN. Univariable models with DNL contours (Tables S10–S12) and LAeqN contours (Tables S13 and S14), in general, had positive associations between noise exposure and socially vulnerable groups (i.e., the socially vulnerable groups were more likely to be exposed).

Table 3. Multinomial multivariable-adjusted odds ratios and confidence intervals [ORs (95% CIs)] for block group exposure to day–night average sound level (DNL) exposure groups (45 to <55 dB(A), 55 to <65 dB(A), ≥65 dB(A)) relative to base group (<45 dB(A)) for a 10% increase in percentage of block group with characteristic.

Variables ($n = 90$ airports; 74,253 block groups)	45 to <55 dB(A)	55 to <65 dB(A)	≥65 dB(A)
Race/ethnicity (%)			
Non-Hispanic black	1.05 (1.04, 1.06)	1.03 (1.01, 1.05)	1.15 (1.06, 1.24)
Non-Hispanic Asian	1.10 (1.09, 1.12)	1.13 (1.10, 1.17)	0.49 (0.35, 0.69)
Hispanic	1.13 (1.11, 1.14)	1.12 (1.09, 1.15)	1.39 (1.25, 1.54)
Non-Hispanic other	1.08 (1.03, 1.13)	1.12 (1.03, 1.22)	1.31 (0.92, 1.87)
Non-Hispanic white	Ref	Ref	Ref
Education (%)			
<High school diploma or GED	1.00 (0.98, 1.02)	1.09 (1.05, 1.14)	0.89 (0.75, 1.04)
High school diploma or GED	1.05 (1.03, 1.07)	1.19 (1.15, 1.23)	1.17 (1.01, 1.36)
>High school diploma or GED	Ref	Ref	Ref
Household income (%)			
<$25,000	1.02 (1.01, 1.04)	1.04 (1.01, 1.07)	1.04 (0.92, 1.18)
$25,000 to <$50,000	1.05 (1.04, 1.07)	1.10 (1.06, 1.14)	1.08 (0.93, 1.25)
$50,000 to <$75,000	1.05 (1.03, 1.08)	1.09 (1.05, 1.14)	1.21 (1.02, 1.44)
≥$75,000	Ref	Ref	Ref

Note: The main model was adjusted for variables on race/ethnicity, education, household income, and airport. GED, General Education Development; Ref, reference.

Discussion

Aggregated across airports, we observed higher odds of exposure to aircraft noise in census block groups with a higher percentage of socially vulnerable groups, including across race/ethnicity, education, and income. However, we observed considerable variability among U.S. airports in these patterns (Figure 3; Figures S1 and S2).

Our findings of higher odds of aircraft noise exposure in census block groups with higher percentage Hispanic populations were similar to results reported for some single airport studies. For example, Ogneva-Himmelberger and Cooperman (2010) investigated sociodemographic characteristics of aircraft noise exposure within a 21-km radius, the maximum extent of the 55-db(A) contour, of Boston Logan International Airport for 1990 and 2000 and found high clusters of Hispanic populations concentrated in noise-affected areas, whereas high clusters of Black populations were concentrated outside the airport area. Sobotta et al. (2007) used a research design that was similar to our study design and also found disproportionate exposure to aircraft noise around an Arizona airport in census blocks with a higher percentage of Hispanic heads of household. The authors found a 25% increase in probability of being within a block group within the 65-dB(A) noise contour compared with being outside the 65-dB(A) contour with each percentage increase in heads of households who are Hispanic. Although we were underpowered to observe associations with the 65-dB(A) noise contour, in part because aircraft engines were much quieter in 2010 (the year of our analysis) than they were in 1992 [the year of the analysis by Sobotta et al. (2007)], we did observe a 5% increase in the odds (per 10-percentage point increase in a block group's Hispanic population) of exposure to noise levels >55 dB(A) and 13% increase in odds of exposure to noise levels >45 dB(A) aggregated across multiple airports.

Further, our results are an aggregate of multiple airports across the United States, and we found substantial heterogeneity by airport (Figures 3; Figures S1 and S2). This heterogeneity may reflect varying histories on how and why airports were sited and how the areas evolved over time as influenced by local geography, zoning policies, and real estate practices. Although FAA oversees the procedural process for conducting noise studies, the planning and decision making related to aircraft noise impacts is made at the local level (Sobotta et al. 2007). Kruize et al. (2007) investigated road, rail, and air traffic noise exposures in the Netherlands and reported an indication of higher exposure with lower income only for road traffic noise. In London, UK, Tonne et al. (2018) found higher exposure to aircraft noise among those of the highest household income, White compared with Asian

Table 4. Within-airport odds ratios and confidence intervals [ORs (95% CIs)] for block group exposure to three different day–night average sound level (DNL) thresholds (i.e., three different models) for a 10% increase in percentage of block group with characteristic using multivariable hybrid mixed-effect logistic model with random intercept by airport.

	Models		
Variables	DNL 45 dB(A) ($n = 86$ airports; 74,170 block groups; 21,296 exposed)	DNL 55 dB(A) ($n = 61$ airports; 34,283 block groups; 3,476 exposed)	DNL 65 dB(A) ($n = 15$ airports; 4,031 block groups; 158 exposed)
Race/ethnicity (%)			
Non-Hispanic black	1.04 (1.03, 1.05)	0.98 (0.97, 1.00)	0.96 (0.89, 1.04)
Non-Hispanic Asian	1.11 (1.09, 1.12)	1.04 (1.00, 1.07)	0.44 (0.30, 0.66)
Hispanic	1.13 (1.11, 1.14)	1.05 (1.02, 1.07)	1.09 (0.96, 1.23)
Non-Hispanic other	1.09 (1.05, 1.14)	1.03 (0.95, 1.12)	0.82 (0.54, 1.25)
Non-Hispanic white	Ref	Ref	Ref
Education (%)			
<High school diploma or GED	1.02 (1.00, 1.04)	1.08 (1.04, 1.13)	1.08 (0.89, 1.30)
High school diploma or GED	1.07 (1.05, 1.09)	1.21 (1.17, 1.26)	1.11 (0.93, 1.32)
>High school diploma or GED	Ref	Ref	Ref
Household income (%)			
<$25,000	1.02 (1.00, 1.03)	0.96 (0.93, 0.99)	0.99 (0.84, 1.15)
$25,000 to <$50,000	1.06 (1.04, 1.08)	1.01 (0.98, 1.05)	1.10 (0.92, 1.31)
$50,000 to <$75,000	1.06 (1.04, 1.08)	1.02 (0.98, 1.07)	1.17 (0.95, 1.43)
≥$75,000	Ref	Ref	Ref

Note: Models were adjusted for variables on race/ethnicity, education, household income, and airport. GED, General Education Development; Ref, reference.

and other populations, and the lowest area-level income deprivation; higher exposure to rail noise with highest area-level income deprivation; and less pronounced socioeconomic and ethnic inequalities related to road traffic noise. Of note, Dreger et al. (2019) reviewed eight studies on noise and social inequality and found mixed results; however, the sources of environmental noise (e.g., road, rail, aircraft, industry noise) and their measurement and use (grouped or individual), as well as the measures and use (indicator or index) of social inequality, varied between studies. A study assessing environmental noise (not an aircraft-specific noise model) for the contiguous United States that used geospatially modeled sound levels, found that higher noise exposure was related to race/ethnicity, SES, and residential segregation (Casey et al. 2017).

We hypothesize that our findings of higher odds of being exposed to noise in census block groups with lower education levels may reflect that these groups may not have opportunity to move out of areas with high exposure (Phinney 2013). In addition, those of higher education may be more likely to have social networks and political connections that allow them to engage in civic organizations and political activism (Banzhaf et al. 2019; Collette 2011) to lobby for policies to lower exposure. Noise as a disamenity can also lower the value of land, or, the lower value of land, related to racism and segregation, could invite certain sectors (Sobotta et al. 2007). However, our observation of higher odds of exposure with greater percentage of population with household incomes \$25,000 to <\$75,000 and those with only a high school education (as compared with the lowest income and education attainment groups, respectively) living near an airport may be due to employment patterns, as well as housing market dynamics (Brainard et al. 2004; Lipscomb 2003; National Academies of Sciences, Engineering, and Medicine 2008).

We focused on three important DNL noise thresholds—45, 55, and 65 dB(A)—and found modest differences by threshold. Although some associations were consistent across thresholds, including with Hispanic status, others varied in interesting ways. For example, in multinomial analysis block groups with higher percentage non-Hispanic Asians had lower odds of exposure to aircraft noise ≥ 65 dB(A) when compared with the base group [i.e., block groups with exposure <45 dB(A)] but had higher odds of exposure to DNL 45 to <55 and DNL 55 to <65 dB(A). The hybrid mixed-effects regression analysis seemed to confirm that this group lives near airports but just outside the 65-dB(A) threshold. Conversely, in ordered multinomial models only, block groups with higher percentage non-Hispanic blacks showed higher odds of exposure to DNL 55 to <65 dB(A) and DNL ≥ 65 dB(A) compared with those exposed to DNL <45 dB(A). This may reflect less distinction in percentage non-Hispanic blacks with block groups exposed to DNL 45 dB(A) to <65 dB(A) than with block groups exposed to DNL <65 dB(A).

We chose to use buffers around airports that were the maximum extent of the noise contours as our areas of study. We also investigated a single year, and patterns may not hold over time—airplanes have become significantly quieter over the years (GAO 2020), so populations affected in 2010 may no longer be affected to the same extent (Ogneva-Himmelberger and Cooperman 2010; GAO 2020). Given that some groups may lack residential mobility or home ownership may change slowly, residential patterns in the 2010 unexposed block groups could be remnants of past exposure. As an alternative approach, we could have chosen a circle of equal area outside the maximum extent of the noise contours so the "unexposed" block groups would not include areas that are close to the airport and affected by distance; however, this method could have resulted in identifying differences more related to urbanization and land-use factors than airports. Differences in urbanization and land-use factors could influence flight paths where flights may be directed over less densely populated areas. Another possible approach would have been to compare sociodemographics of those exposed with the sociodemographics of the corresponding metropolitan statistical area (MSA). The MSA delineates metropolitan areas composed of an urban area with a population nucleus of $\geq$50,000 inhabitants along with adjacent communities that are significantly economically and socially connected (U.S. Census Bureau n.d.-e). However, our method allowed us to examine more geographically proximate populations to control for broader population differences and facilitated comparability with other studies (Sobotta et al. 2007).

Our study had several limitations. We used DNL, which is an annualized noise exposure metric based on a typical 24-h day, as the basis of our primary regression models. However, this may not be the ideal metric associated with annoyance or health effects, and some have suggested that other noise metrics, such as number of aircraft overflights, are more correlated with annoyance than DNL (Collette 2011). Those with DNL below, for example, 65 dB(A), could have periods of exposure within a given year that are >65 dB(A). This is particularly true for areas surrounding airports with intersecting runways designed to accommodate expansion or variable wind direction (Yu and Hansman 2019). In the latter scenario, residents along the flight path that is used for the less frequent wind direction could have periods of high aircraft noise exposure equal to those along the path of the primary runway; however, their annualized exposure could be below the threshold. Our investigation of nighttime noise levels (LAeqN), though, showed similar results to the DNL analysis.

Using census block group-level data raises the issue of the precision of the sociodemographic distribution of the populations within a block group (Banzhaf et al. 2019; Jones et al. 2014). ACS data at the block group level can have large standard errors; the distribution of CVs we calculated for the block groups used were largely categorized as having medium and low reliability. Aggregating data, either by attribute or geography, is a simple approach to reducing the standard error but it comes at the cost of lowering the resolution of population sociodemographics and exposure assignment (Spielman et al. 2014). We chose to analyze noise exposures without aggregating ACS data geographically; however, future analyses could be done to see if the patterns that we found hold using tracts or larger geographic units. In addition, the size of the area delineating the block groups could vary around airports; for example, they could be smaller in very densely populated areas (Banzhaf et al. 2019), which was not accounted for in our analysis. However, our intention was not to make inferences about individuals (Idrovo 2011) but, rather, to elucidate noise exposure patterns at the population level. Utilizing larger geographic units would have implicitly assumed uniform patterns within, for example, census tracts instead of block groups, which would have contributed error given the relative steep gradients of some noise contours.

Relatedly, in overlaying noise contours with census block groups, there are some block groups with part of the block group inside the noise contour area and part outside the area. We made the decision that if $\geq 50\%$ of the (land) area of that block group was within the noise contour then the entire census block group would be considered exposed. The noise exposure models excluded helicopter operations, which can be a major source of aviation noise in certain communities, such as those surrounding trauma centers. Although peer-reviewed guidance for integrated modeling techniques for predicting fixed-wing aircraft noise is well established, such guidance is yet to be stipulated for predicting helicopter noise (Page 2016). Our analyses did not account for noise abatement measures, which may be important when thinking about noise exposure rather than ambient sound levels. We did not report on patterns of racial segregation (Morello-Frosch 2002), which may be an important aspect of the sociodemographic patterning of noise exposure in the United States. More generally, we relied on racial and ethnic categorizations from the census, but these data have limitations and do not fully capture the root causes of exposure differentials related to racism, racial discrimination, and racial segregation (Payne-Sturges et al. 2021). In addition, there is a complex relationship between race/ethnicity and SES (Williams et al. 2016), and although we controlled for both in the same model, we did not evaluate effect measure modification.

In spite of these limitations, our study offers multiple novel insights. To our knowledge, we have performed the first evaluation of sociodemographic patterning of aircraft noise exposure across multiple (90) U.S. airports. In addition, the noise modeling for the 90 airports was performed in parallel with similar model inputs and assumptions using a regulatory-approved software (i.e., AEDT). The inclusion of multiple airports using a common analytical approach gave us more power to detect differences and makes the study more generalizable. We also applied statistical techniques that accounted for clustering around airports and explored within- and between-airport differences, and our results were robust across various regression approaches. Our study highlighted that there was considerable heterogeneity between airports, reinforcing that results from single- or few-airport studies should not be extrapolated to the entire United States. Our analysis was at the block group level, and not at the level of larger geographic units (e.g., counties). At higher geographic levels, if segregation exists between the geographic units or if the boundaries of geographic units are systematically gerrymandered, associations between noise exposure and sociodemographics could be overestimated (Banzhaf et al. 2019).

Conclusion

We found that, in pooled multivariable analysis, increasing higher exposure categories of DNL $45\text{ to }<55$, $55\text{ to }<65$, and $\geq 65\,\mathrm{dB(A)}$ relative to a base category of $<45\,\mathrm{dB(A)}$ and DNL noise exposures above the 45-dB(A) and 55-dB(A) thresholds were positively associated with block groups with higher percentages of socially vulnerable populations; however, there was substantial heterogeneity in associations by airport. Understanding these patterns and differences in noise exposure is important for nationwide studies on the associations of noise and health, especially given potential confounding in such studies. Airport-specific associations can provide valuable insight for local policy makers considering environmental justice issues but should not be generalized to other airports or nationally given heterogeneity in the associations.

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