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Residential and GPS-defined activity space neighborhood noise complaints, body mass index and blood pressure among low-income housing residents in New York City

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Abstract

Little is known about how neighborhood noise influences cardiovascular disease (CVD) risk among low-income populations. The aim of this study was to investigate associations between neighborhood noise complaints and body mass index (BMI) and blood pressure (BP) among low-income housing residents in New York City (NYC), including utilizing global positioning system (GPS) data. Data came from the NYC Low-Income Housing, Neighborhoods and Health Study in 2014, including objectively measured BMI and BP data (N=102, Black=69%), and one week of GPS data. Noise reports from “NYC 311” were used to create a noise complaints density (unit: 1,000 reports/km²) around participants' home and GPS-defined activity space neighborhoods. In fully-adjusted models, we examined associations of noise complaints density with BMI (kg/m²), and systolic and diastolic BP (mmHg), controlling for individual- and neighborhood-level socio-demographics. We found inverse relationships between home noise density and BMI (B=-2.7 [kg/m²], p=0.009), and systolic BP (B=-5.3 mmHg, P=0.008) in the fully-adjusted models, and diastolic BP (B=-3.9 mmHg, P=0.013) in age-adjusted models. Using GPS-defined activity space neighborhoods, we observed inverse associations between noise density and systolic BP (B=-10.3 mmHg, p=0.019) in fully-adjusted models and diastolic BP (B=-7.5 mmHg, p=0.016) in age-adjusted model, but not with BMI. The inverse associations between neighborhood noise and CVD risk factors were unexpected. Further investigation is needed to determine if these results are affected by unobserved confounding (e.g., variations in walkability). Examining how noise could

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be related to CVD risk could inform effective neighborhood intervention programs for CVD risk reduction.

Keywords

Neighborhood noise exposure; low-income housing residents; geographic information systems; global positioning systems; health disparities

Introduction

Obesity and hypertension, the major risk factors for cardiovascular disease (CVD), stroke, and type 2 diabetes [1], have become looming public health issues in the United States. In the U.S., over 70 % of adults aged 20 years are overweight or obese [2]. Approximately 31% (68 millions) of the U.S. adults (aged 18 years) have hypertension and 70% (48 millions) of them had received its treatment.[3] While the prevalence of obesity [4] and hypertension [5] has virtually remained high over the past decade, there are significant disparities in these negative health conditions [6]. Specifically low-income individuals disproportionately experience CVD health disparities [7, 8].

The causes of obesity and hypertension are thought to be multifactorial ranging from individual (e.g., attitude, beliefs), through interpersonal (e.g., family, peers, social network), to environmental factors (e.g., built and food environments) [9-11]. There is a need to investigate how neighborhood environments influence CVD risk, especially for socially disadvantaged individuals [12, 13]. In particular, neighborhood noise is an important factor that is an understudied neighborhood exposure, which may play a role in population health and health disparities. However, empirical research has indicated that exposure to noise from various sources (e.g. residential neighborhoods, workplaces) is associated with CVD risk, including obesity and hypertension [14-16], but other studies indicated no associations [17, 18]. For instance, one recent study on the relationship between occupational noise and obesity using the 2014 National Health Interview Survey (NHIS) indicated that individuals who were exposed to occupational noise had 46% greater odds of being obese compared to those who never exposed [14]. Another recent study on traffic noise exposure and self-reported body mass index (BMI) among Bulgarian adults reported a 3% increase in being obese in the total sample and 5% increase in being obese in individuals who lived for 20 years [15]. In contrast, a recent study on road traffic noise among a population-based sample of adults in France indicated that residential noise exposure was not associated with BP [17]. No neighborhood noise studies to date have been conducted among low-income populations in an urban area, which highlights the significant need for this study in the literature. Moreover, previous studies have most often focused on occupational noise sources or on transport-related noise, less frequently on noise sources from the social environment, a gap that the present study attempts to address.

Neighborhood noise sources can be assessed in multiple ways in spatial epidemiology research. The majority of the previous research relied on crude definitions of neighborhoods, such as administrative boundaries (e.g. ZIP code, census tract) [19, 20] and static spatial buffers around a geographic location (e.g. 400-m or 800-m circular buffers) [19]. In previous

research on neighborhood noise, 50 m to 1000 m static buffers were used to assess neighborhood noise level [21, 22]. This is the case with the existing research on neighborhood noise and CVD risk. However, with emerging technology, new methods for studying neighborhoods have been developed. These include Global Positioning System (GPS) device, which allows researchers to define neighborhoods more accurately, giving a reflection of what is called “activity space neighborhoods” rather than residential neighborhoods. This method better captures neighborhood contexts corresponding to an individual’s daily mobility [23, 24], reducing the possibilities for spatial misclassification, which leads to incorrectly characterizing a neighborhood-level exposure [25]. Our recent study on spatial misclassification in the exposure to neighborhood noise complaints among low-income residents in New York City (NYC) using GPS data shows that measurements of the count neighborhood noisy events around residential area differs from the ones around GPS-defined activity space neighborhoods [26]. Therefore, the purpose of this study is to examine the associations between neighborhood noise complaints, BMI and BP among a sample of low-income housing residents in NYC, including utilizing GPS data. We hypothesized that neighborhood noise complaints would be positively associated with BMI and BP.

Methods

Study participants

We used data from the NYC Low-Income Housing, Neighborhoods and Health Study (N=120). We recruited low-income housing residents in NYC through community-based outreach (e.g., handing out and posting flyers near public housing developments in NYC). Inclusion criteria to participate in this research was: 1) if they were at least 18 years, 2) if they reported living in low-income housing in NYC, 3) if they could speak and read English, 4) reported if they were not being pregnant, 5) reported no limitations in walking or climbing stairs, and 6) were willing to carry global positioning system (GPS) device for one week. Predominantly, the participants (80%) lived in public housing relative to other low-income housing. We collected the data from June to July 2014. We obtained informed consent from all participants before data collection. All procedures and study protocol for this study were reviewed and approved by the New York University School of Medicine Institutional Review Board. Further detailed data collection and procedures have been described in the previous studies [27, 28].

GPS and GIS data and processing

During the study orientation along with the baseline assessment, participants were instructed how to wear the GPS device (QStarz BT-Q1000XT GPS, Qstarz International Co., Ltd., Taipei, Taiwan) all the time except while sleeping, bathing, or swimming for one week, which was consistent with the prior studies [29, 30]. Participants were also asked to respond to the series of questions for a travel diary, e.g., “Did you charge the GPS monitor?” GPS data were recorded at 30-second intervals. Research staff received the devices from participants, either meeting at public locations (e.g., library, coffee shop), or the project office. Participants followed the study’s GPS protocol as described previously [27, 29].

We downloaded GPS data through Qstarz GPS device and transferred into a geodatabase as to process, create maps, and store the data. We removed GPS data that were errors and duplicated time-stamps. Among 120 participants, we identified that six participants had no GPS data because of battery problems, user error, or failing to return the device. We were not able to link the five participants' survey data to GPS data. One participant had insufficient data and another participant's ID was a duplicate. Further, we removed five participants' data because they spent the majority of time away from NYC, which resulted in the total analytic sample of 102 participants. The detailed data processing procedures were described previously [27, 29]. In addition, while 120 participants is a relatively small sample size for general population health and health disparities research, given that many recent GPS studies have fewer than 100 participants; our sample size exceeds the sample sizes of most existing GPS-based research. For instance, according to the recent review the application of GPS technology in neighborhood environment studies, our sample size is considered to be adequate [31].

We created 200 meter (m) and 400 m GPS-defined (i.e., “activity space” or “daily mobility path”) straight-line buffers around each participant's GPS data (Figure 1). This method is often used in behavioral geography to better understand where individuals go and are exposed to neighborhood environments [30, 32]. In this study, we also used 200 m and 400 m circular and street network buffers around the participants' home addresses, which we geocoded using standard methods [27, 29]. All GIS processing was performed by using ArcGIS version 10 (ESRI, Redlands, CA).

Neighborhood noise

We created a density per km² of neighborhood noise complaints using NYC 311 data, which was initiated in 2010 by NYC Department of Environmental Protection [33]. NYC 311 is a sampling platform that NYC residents can call or use a NYC 311 cellphone application to report a complaint in their neighborhoods. In this study, we used the noise complaint reports between January 1, 2014 and December 31, 2014 (n=145,067 reports) because we collected the data (including GPS data) in 2014. The NYC 311 noise complaint reports were time-stamped, along with a latitude and longitude of a noise where it occurred, address, streets, city, and borough. The types of noise include loud music/party, construction, loud talking, car/truck music, and barking dog, among others. Due to missing in a latitude and longitude coordinate, some reports (n=1,100) were removed from the sample, which resulted in a total 143,967 geocoded noise reports. Previous studies have utilized the NYC 311 noise complaint data [34, 35], which can be regarded as pollution indicators for the location of noise incidence from residents in NYC [35]. The density of noise complaints in their neighborhood was defined as the counts of noise reports within the buffers described above (i.e., circular, network, and GPS-defined activity space buffers) divided by the total area of the buffer per km² (unit: 1,000 noise complaints/km²).

Body mass index (BMI) and blood pressure (BP)

Participant's height and weight were objectively measured by trained research assistants. We computed BMI for each participant: weight in kilograms/(height in meter)². In addition, participants were instructed to sit in a back supported chair during the measurement of BP

while they were outstretching their arms and were not crossing their legs [36-38]. Approximately 15-30 seconds after participants seated, research assistants measured participant's systolic and diastolic BP (millimeter of mercury [mmHg]) using a Welch Allyn Vital Signs 300 monitor.

Covariates

Age (18-24, 25-44, and 45+), gender (male/female), race/ethnicity (Black, Hispanic, and Other [including White, Asian, and other]), educational attainment (less than a 12th grade education, high school degree and some college or more), and employment status (full-time, part-time, or not working) were controlled for in multivariate models as individual characteristics. As neighborhood characteristics using data from the 2010 U.S. Census and the 2009-2013 American Community Survey, percent of non-Hispanic Black residents at a census block group, and median household income at the census block group level were controlled.

Statistical analysis

We performed descriptive statistics for all variables. Subsequently we examined associations between density of noise complaints and BMI, systolic BP and diastolic BP. We examined this association for 200 m and 400 m circular and network buffers around participant's home as well as GPS-defined activity space buffers using multivariable models. To account for neighborhood clustering effect, we estimated all the models with clustered robust standard errors (using census-block group). We estimated age-adjusted and fully-adjusted models. Covariates for fully-adjusted models include age, gender, race/ethnicity, education, employment status, total household income, census block group percent non-Hispanic black, and census block median household income. We conducted all statistical analyses using SAS version 9.4 (Cary, NC).

Results

Individual and neighborhood characteristics

Forty-two percent of participants were 45 years or older. More than half of participants were male (n=53) and predominantly Black (69%) (Table 1). Seventy-three percent had at least high school diploma, approximately 28% earned at least \$25,000 per year, and were 13% full-time employment. The average BMI was 29.8 (SD ± 7.95). Average systolic and diastolic BP were 130.9 (SD±17.9) and 77.7 (SD±12.2).

Neighborhood noise complaint densities within a 200 m and 400 m circular buffer around participant's home were of 1054.3 (SD± 1073.2) and 813.6 (SD± 577.0) complaints per km², respectively, while densities within a 200 m and 400 m network buffer around home were of 1696.0 (SD± 1804.8) and 1196.3 (SD± 859.6) complaints per km², respectively. The noise density for the GPS-defined activity space with a 200 m and 400 m buffer was 862.9 (SD ±384.2) and 812.2 (SD± 332.7), respectively. Census block group percent non-Hispanic Black was 31.5% and census block group household income was \$44,003.

Associations between density of noise and body mass index and blood pressure

Overall, we found consistent inverse relationships between neighborhood noise complaint density and BMI in age- and fully-adjusted models (Table 2). For example, in the fully-adjusted model, density of noise complaints was inversely associated with BMI within 400 m circular and network buffer around home ($B=-2.72$ (kg/m^2) [95% Confidence Interval (C.I.) = -4.71, -0.72], $p=0.009$) and ($B=-1.72$ (kg/m^2) [95% C.I. = -3.02, -0.42], $p=0.011$), respectively. However, we did not find associations with GPS-defined activity space buffers.

We generally found inverse associations between density of noise complaints and systolic BP in the fully-adjusted models for the home circular and GPS-defined activity space buffers, but not for the home network buffers (Table 3). For instance, in the fully-adjusted model, density of noise complaints was inversely associated with systolic BP within 400 m home circular and GPS-defined buffers ($B=-5.34$ mmHg [95% C.I. = -9.24, -1.45], $p=0.008$) and ($B=-10.33$ mmHg [95% C.I. = -18.86, -1.81], $p=0.019$), respectively. The associations between noise complaint density within network buffers and systolic BP were of weaker magnitude.

We found inverse associations between density of noise complaints and diastolic BP in the age-adjusted models with home circular buffer and GPS-defined activity space buffers, but not for the home network buffers. For instance, in age-adjusted model, density of noise complaints was inversely associated with systolic BP within 400 m home circular buffer and GPS-defined buffer ($B=-3.94$ mmHg [95% C.I. = -7.00, -0.88], $p=0.013$) and ($B=-7.506$ mmHg [95% C.I. = -13.55, -1.46], $p=0.016$), respectively. The associations between noise complaint density within network buffers and diastolic BP were much weaker.

Discussion

We examined associations between the density of noise complaints in residential areas and GPS-defined areas and BMI as well as systolic BP and diastolic BP among a sample of low-income housing residents in NYC. Overall, we found that there are consistent inverse associations between neighborhood noise complaints (unit: 1,000 complaint reports per kilometer square) with circular and network buffers around home and BMI, but not for GPS-defined buffers. These findings suggest that residential noise complaints may matter more than noise complaints elsewhere in one's activity space. Additionally, there were inverse associations between noise complaints within home circular and GPS-defined buffers and systolic BP in fully-adjusted model as well as associations between neighborhood noise complaints within home circular and GPS defined buffers and diastolic BP in age-adjusted, yet not with home network buffers. One could argue that noise would diffuse and would not follow the street network, unlike stores along with the streets. These inconsistent associations could potentially be related to underlying mechanism (e.g. stress) that has not been investigated.

Our findings on inverse associations between neighborhood noise complaints within residential buffers (i.e., circular and network buffers) and BMI are inconsistent with prior research [14-16, 18]. For example, one recent study on long-term noise exposure in relation to BMI using the 2014 National Health Interview Survey data in the U.S. general population

found that individuals who were exposed to long-term occupational noise (15 years) had 0.97 (kg/m²) higher BMI compared to ones with no exposure [14], which is potentially related to the very different exposure that was used in our study. In our study, neighborhood noise complaint density was also inversely associated with BP. However, a review study on noise exposure (again based on a very different exposure assessment) and BP has indicated that there is a statistically significant positive association between occupational noise exposure and systolic and diastolic BP (3.9 and 1.7 mmHg increases, respectively), but not for road traffic noise [39]. One study on road, rail, and air transportation noise exposure in relation to BP among 7,290 participants of the residential and workplace neighborhoods and blood pressure (RECORD Study) reported that exposure to noise at residential areas is not associated with BP [17].

There are several potential explanations for our findings. Possible explanations may be 1) the small and selective study participants, 2) difference in noise exposure assessment (our assessment targeting a very different construct related to more social sources of noise), 3) geographic locations, and 4) confounding by other factors. First, the size of our participants is small and the sample is selected because participants were recruited from low-income housing in NYC. However, other studies are population-based samples, such as the U.S. adults from the 2014 NHIS [14], two studies from Sweden [16, 18], one from France [17]. A second possible explanation could be difference in noise assessment as our noise data came from NYC 311 that any NYC residents can file a complaint report in a specific neighborhood across NYC. Generally, the location of noise complaint is close to a residence of the person who reports. The noise complaints increase where many residents reside as well as populous area in NYC such as midtown, lower Manhattan, or near clubs. In contrast, previous studies measured noise via self-reported survey [14] or objectively measured noise on road, rail, and air transportation noise [16-18]. It should be emphasized that, while most previous studies focused on occupational or transport-related noise, the present study was innovative in its focus sources of noise more often related to the social environment. Third, geographic locations may be another possible explanation. Highly populous city such as NYC differs from studies done in suburban or semi-rural city in Sweden [16, 18], urban city in Bulgaria [40] or a population-based sample of U.S adults [14]. The true associations may differ according to the geographic context. Fourth and finally, the associations that were estimated may be confounded by factors that were not controlled for, including urbanicity, which can be linked to low BMI and BP due to higher walkability than suburban cities. Other unobserved confounding could also potentially relate to higher BMI and BP, such as social norms towards eating behaviors.

There are several limitations that need to be noted. First, our findings may not be generalizable to non-low-income residents in NYC, low-income residents who reside in non-urban cities in the U.S., as well as non-English speaking low-income residents. Second, although we objectively measured BP by our research staff, we measured it only once. As a clinical BP assessment, typically two or more measurements are required. Thus, one BP measurement may over- or under-estimate the BP in our sample. Third, our findings are based on a cross-sectional design. Thus, reverse causation can also be potential in our study. Fourth, urban cities such as NYC with many high-rise buildings could obstruct GPS satellite signals. Because of this issue, some GPS coordinates may be lost and such data are not used

in our study. Fifth, in our study, we used all available noise complaint report in 2014 and each complaint was regarded as one case irrespective of the type of noise (e.g., loud music versus construction), duration of the noise (e.g., specific time of day versus more than a week), and unit of analysis (e.g., a noise complaint report as one case versus averaged noise complaint reports per week) in the neighborhood. Thus, these analytical considerations could impact the estimates of noise on each participant. Six, noise complaints often occur during the morning and evening when residents in NYC come back from work. Therefore, the density of noise may vary across place and time of day.

Conclusion

This study contributes to the sparse literature examining both neighborhood noise and noise from GPS-defined activity buffers. Our findings suggest that higher density of noise complaints is related to lower BMI, systolic and diastolic BP among a sample of low-income housing residents in NYC. The results are counter intuitive, compared to what we would have hypothesized. Highly populous area such as NYC would produce more noise compared to rural cities in the US. The result may differ if we conduct the similar study on GPS tracking and residential areas on individuals who come from low-income households living in rural areas and examine associations between neighborhood noise and BMI and BP. Further research is needed to examine how neighborhood noisy events related to social environments are associated with CVD risk among low-income housing residents to inform more effective place oriented environmental interventions and policy for cardiovascular risk reduction.

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Figure 1. Locations of noise complaint reports data and residential buffers and GPS-defined activity space neighborhoods in New York City, 2014.

Note: Participant home geodesic buffers represent circular buffers around participants' home. Participant home GIS network buffers represent street network buffers around participants' home.

Table 1

Individual socio-demographic and health-related, and neighborhood characteristics of participants in New York City, 2014 (n=102).

Individual characteristics	Description	n (%)
Age	18-24 years	23 (22.55)
	25-44 years	37 (36.27)
	45+ years	42 (41.18)
Gender	Male	53 (51.96)
	Female	49 (48.04)
Race/ethnicity*	White	5 (5.00)
	Black	69 (69.00)
	Hispanic	22 (22.00)
	Other*	4 (4.00)
Education	< High school	27 (26.47)
	High school	44 (43.14)
	Some college	24 (23.53)
	Undergraduate or graduate degree	7 (6.86)
Total household income*	< \$25,000	73 (72.28)
	\$25,000-\$49,999	21 (20.79)
	\$50,000+	7 (6.93)
Employment status*	Full-time	13 (13.00)
	Part-time	18 (18.00)
	Unemployed	57 (57.00)
	Retired or school	12 (12.00)
BMI		29.84 (7.95)
Blood pressure	Systolic	130.90 (17.90)
	Diastolic	77.73 (12.23)
Neighborhood characteristics		Mean (SD)
Density of noise complaints	200 m circular buffer	1054.32 (1073.22)
	400 m circular buffer	813.56 (577.04)
	200 m network buffer	1696.02 (1804.81)
	400 m network buffer	1196.28 (859.59)
	200 m GPS activity buffer	862.89 (384.22)
	400 m GPS activity buffer	812.24 (332.74)
Socio-demographics	% non-Hispanic Black	31.50 (21.26)
	Household income	44,003.45 (28,029.67)

Note: Analytic sample (N=102) is based on when outcomes are no missing.

* Race/ethnicity, total household income, employment status are missing with 2, 1, and 2 participants, respectively.

Table 2
Associations between density of noise within each buffer and BMI among 102 participants in New York City, 2014

Density of noise ^d Size and type of buffer	BMI					
	Age-adjusted			Fully-adjusted		
	β	95% C.I. ^b	<i>p</i>	β	95% C.I.	<i>p</i>
200 m circular	-1.09	-2.14, -0.03	0.043	-1.19	-2.62, -0.02	0.093
400 m circular	-2.42	-4.51, -0.32	0.025	-2.72	-4.71, -0.72	0.009
200 m network	-0.69	-1.23, -0.15	0.013	-0.83	-1.62, -0.04	0.040
400 m network	-1.50	-2.91, -0.08	0.039	-1.72	-3.02, -0.42	0.011
200 m GPS	-0.90	-4.72, 2.91	0.635	-1.97	-5.31, 1.37	0.241
400 m GPS	-0.94	-5.37, 3.50	0.673	-2.41	-6.09, 1.28	0.195

Note:

^aBased on per 1,000 noise complaint reports.

^bC.I. = Confidence Interval.

Table 3
Associations between density of noise within each buffer and systolic and diastolic blood pressure among 102 participants in New York City, 2014

Density of noise ^a Size and type of buffer	Systolic blood pressure					
	Age-adjusted			Fully-adjusted		
	β	95% C.I. ^b	<i>p</i>	β	95% C.I.	<i>p</i>
200 m circular	-1.28	-3.41, 0.86	0.234	-2.34	-4.43, -0.25	0.029
400 m circular	-3.69	-8.10, 0.72	0.099	-5.34	-9.24, -1.45	0.008
200 m network	-0.64	-2.00, 0.73	0.352	-1.22	-2.57, 0.13	0.075
400 m network	-2.06	-5.08, 0.96	0.177	-2.48	-5.26, 0.31	0.080
200 m GPS	-6.62	-14.15, 0.90	0.083	-7.48	-14.06, -0.91	0.027
400 m GPS	-8.53	-17.45, 0.40	0.061	-10.33	-18.86, -1.81	0.019
	Diastolic blood pressure					
Density of noise ^a Size and type of buffer	Age-adjusted			Fully-adjusted		
	β	95% C.I.	<i>p</i>	β	95% C.I.	<i>p</i>
200 m circular	-1.61	-3.28, 0.049	0.057	-1.62	-3.32, 0.08	0.061
400 m circular	-3.94	-7.00, -0.88	0.013	-3.67	-12.18, 8.09	0.687
200 m network	-0.62	-1.83, 0.59	0.305	-0.59	-1.72, 0.54	0.298
400 m network	-1.95	-4.30, 0.41	0.103	-1.32	-4.15, 1.51	0.353
200 m GPS	-5.99	-10.85, -1.14	0.017	-3.91	-10.58, 2.78	0.246
400 m GPS	-7.51	-13.55, -1.46	0.016	-5.08	-12.93, 2.78	0.200

Note:

^aBased on per 1,000 noise complaint reports.

^bC.I. = Confidence Interval.