Social inequalities in residential exposure to road traffic noise: An environmental justice analysis based on the RECORD Cohort Study

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Accepted 4 November 2010
Published Online First 27 January 2011

ABSTRACT

Objectives To explore social inequalities in residential exposure to road traffic noise in an urban area.

Methods Environmental injustice in road traffic noise exposure was investigated in Paris, France, using the RECORD Cohort Study (n=2130) and modelled noise data. Associations were assessed by estimating noise exposure within the local area around participants' residence, considering various socioeconomic variables defined at both individual and neighbourhood level, and comparing different regression models attempting or not to control for spatial autocorrelation in noise levels.

Results After individual-level adjustment, participants' noise exposure increased with neighbourhood educational level and dwelling value but also with proportion of non-French citizens, suggesting seemingly contradictory findings. However, when country of citizenship was defined according to its human development level, noise exposure in fact increased and decreased with the proportions of citizens from advantaged and disadvantaged countries, respectively. These findings were consistent with those reported for the other socioeconomic characteristics, suggesting higher road traffic noise exposure in advantaged neighbourhoods. Substantial collinearity between neighbourhood explanatory variables and spatial random effects caused identifiability problems that prevented successful control for spatial autocorrelation.

Conclusions Contrary to previous literature, this study shows that people living in advantaged neighbourhoods were more exposed to road traffic noise in their residential environment than their deprived counterparts. This case study demonstrates the need to systematically perform sensitivity analyses with multiple socioeconomic characteristics to avoid incorrect inferences about an environmental injustice situation and the complexity of effectively controlling for spatial autocorrelation when fixed and random components of the model are correlated.

INTRODUCTION

Road traffic noise is the main source of community noise in the urban environment and represents a major environmental risk affecting a large population worldwide. According to the WHO, about 40% of the population of the European Union are exposed to road traffic noise levels exceeding 55 dB(A) during the day, and 20% are exposed to levels above 65 dB(A).[1]

Long-term residential exposure to road traffic noise is associated with stress-related health effects[2 3] such as hypertension and myocardial infarction,[4–7] highlighting the substantial public health impact of this environmental pollution.[8]

What this paper adds

- Previous environmental justice studies have concluded that disadvantaged populations are exposed to higher noise levels in their residential environment than affluent populations.
- However, in this study we found that people living in advantaged neighbourhoods were exposed to higher levels of road traffic noise compared to their deprived counterparts in the city of Paris, France.
- Associations were highly sensitive to the definition of citizenship status, demonstrating the need to systematically perform careful sensitivity analyses with various socioeconomic factors to avoid drawing incorrect conclusions.
- Substantial collinearity between the explanatory variables and spatial random effects may lead to identifiability problems preventing effective control for spatial autocorrelation and resulting in biased and unreliable associations.
- As differential exposure to noise may generate disproportionate health effects among socioeconomic groups and ethnic communities, future socio-epidemiological studies should take into account this environmental risk as a potential factor contributing to social health inequalities.

From a social epidemiology perspective, noise may also contribute to social health inequalities through an uneven distribution of exposure among socioeconomic groups.[9 10] Overall, the few studies that have explored social disparities in noise exposure concluded that socially disadvantaged people (or those living in deprived neighbourhoods) were likely to be exposed to higher noise levels than their well-off counterparts,[11–16] although an opposite association (ie, greater exposure for affluent populations) was also reported.[11 15] These findings are consistent with the concept of environmental injustice whereby low-income groups and ethnic minority populations bear a disproportionate share of environmental hazards.[17] However, despite this apparent consensus, the heterogeneity in the exposure assessment approaches, the choice of spatial analysis levels or the analytical strategies, limits the comparability and generalisability of these results.[17] Furthermore, contrary to the recommendations made in our previous environmental justice study,[18] none of the area-based associations were adjusted for spatial autocorrelation.

The aim of this study was to assess social inequalities in road traffic noise exposure in an urban area. A key feature of this analysis was estimating noise exposure within the local activity space around the residence of study participants. As recommended,[18–20] we attempted to model individual noise exposure across the city of Paris, France, controlling for spatial autocorrelation in noise levels and considering a large variety of socioeconomic characteristics estimated at both the individual and the neighbourhood level. The socio-epidemiological perspective of this environmental justice analysis allows discussion of the mechanisms through which noise exposure might contribute to social health inequalities.

METHODS

Study population

The RECORD (Residential Environment and CORonary heart Disease) Cohort Study has been described in detail elsewhere.[21 22] Briefly, 7290 participants aged 30–79 years were recruited during a free medical check-up conducted by the Centre d'Investigations Préventives et Cliniques in the Paris metropolitan area between March 2007 and February 2008. Participants benefited from a preventive medical examination, offered every 5 years by the French National Health Insurance System for Salaried Workers to all working and retired employees and their families (corresponding to 95% of the population of the Paris metropolitan area) and were accordingly generally healthy (health problems were not considered as exclusion or inclusion criteria). Inclusion criteria were age, ability to fill out study questionnaires, and residence in one of 10 (out of 20) administrative divisions of Paris or 111 other municipalities of the metropolitan area selected a priori.

Participants were accurately geocoded on the basis of their residential address in 2007–2008. Research assistants corrected all incorrect or incomplete addresses with the participants by telephone. Extensive investigations with local urban planning departments were conducted to complete the geocoding. Precise spatial coordinates and block group codes were identified for 100% of participants. The study protocol was approved by the French Data Protection Authority.

In this study, due to noise data availability, only participants living in the city of Paris were considered. Therefore, 2130 participants residing in 571 different neighbourhoods were included in the analyses.

Noise exposure assessment

Road traffic noise levels in 2007 were modelled across Paris by the noise monitoring agency of the City of Paris in accordance with the requirements of the European Environmental Noise Directive,[23] using the EASYMAP model (SIRIATECH, Roubaix, France). This model integrates (1) the environmental noise prediction software MITHRA (Scientific and Technical Centre for Building, Grenoble, France), (2) the geographical information system ArcGIS (ESRI, Redlands, California, USA) and (3) the environmental management information system Drag&Fly (SIRIATECH, Roubaix, France) to generate noise calculations and noise mapping across Paris in two or three dimensions.

Noise calculations were determined using annual average daily traffic data including information on traffic intensity (average number of vehicles per day travelling on each road segment), traffic composition (percentage of light and heavy vehicles), traffic type (congested or not) and traffic speed. Traffic information was available for all main roads, while fixed values were assigned to secondary roads. Traffic data were provided by the Directorate of Roads and Transport of the City of Paris for the years 2006–2007. Other main input parameters included: (1) distance and angles to roads; (2) geometry of buildings and roads (density of buildings and roads, height and dimensions of buildings, width of roads); (3) type of road surface (hard vs soft surface; eg, asphalt, concrete, cobblestone); (4) location of noise barriers; (5) topography; (6) meteorological factors; and (7) various scenarios concerning phenomena of sound reflection and diffraction. These different data were obtained from the Directorate of Roads and Transport of the City of Paris, the National Geographic Institute and other local authorities. Successive model calibrations in various sound environments (quiet or noisy) were performed so as to select the most relevant input parameters for noise modelling in Paris. From all these data, the model estimated noise levels at a spatial resolution of 2×2 m at 1.5 m above ground level. Figure 1 shows the spatial distribution of road traffic noise and the location of the 2130 participants across Paris. The validity of EASYMAP predictions was assessed by comparing acoustic measurements with noise calculations for various locations. Measured and calculated values differed on average by only 1 dB(A).

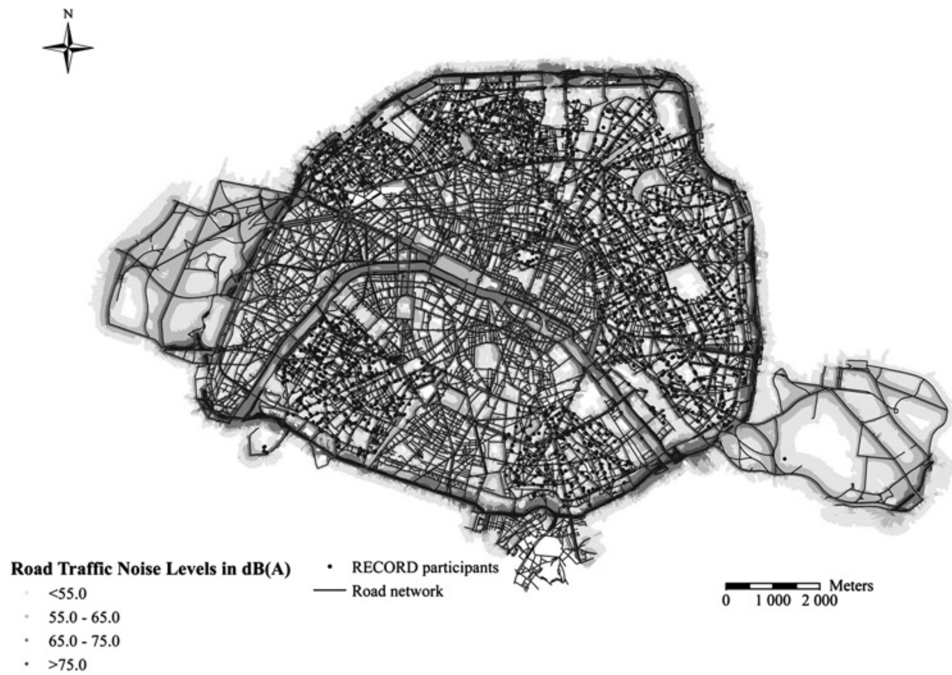
In compliance with the Environmental Noise Directive,[23] the European standard *Lden* measure (day-evening-night level) was used as noise indicator. This indicator is defined as the A-weighted equivalent continuous noise level (L_{Aeq}) over a 24 h period but in which levels during the evening ($L_{Aeq,18:00-22:00}$) and night ($L_{Aeq,22:00-6:00}$) are increased by 5 dB(A) and 10 dB(A), respectively. 'A-weighted' means that the sound pressure levels are adjusted to account for differences in hearing sensitivity at different sound frequencies. Noise levels below the threshold value of 45 dB(A) were recoded as equal to 45 dB(A); this value reflects the lowest sound levels that can be measured in an urban setting.

For each participant, we assessed exposure to road traffic noise within a 250 m radius circular buffer centred on his/her exact residential building by averaging calculation points included within the buffer. This approach was used to estimate individual noise exposure in the local space of outdoor activity. In most places in Paris, people are likely to find a large number of basic services within a 250 m radius around their residence. This exposure estimate was not conceptualised as a surrogate of the overall individual exposure to noise, but rather as one of the components of the total exposure. As previously recommended,[17–20] we assessed the influence of the definition of the outcome (noise indicator) and the spatial scale (size of the circular buffer) on the results by performing sensitivity analyses with: (1) another noise indicator (*Lday*; ie, A-weighted average sound level over the 12 h day period; $L_{Aeq,6:00-18:00}$); and (2) various sizes of the circular buffer (see online appendix 1).

Individual and neighbourhood socioeconomic variables

The following individual characteristics of study participants (described in online appendix 2) were considered: age, education, household income, occupation, dwelling ownership, country of citizenship and country of birth. As suggested by Merlo,[24] we also assigned to each participant the 2004 Human Development Index (HDI) of his/her country of citizenship as a proxy of the country's social development level. Following the United Nations Development Programme,[25] we created a variable coded in four categories so as to distinguish (1) French citizens (HDI=0.942) from (2) citizens from low human development countries (HDI<0.5), (3) citizens from medium human development countries (0.8>HDI≥0.5) and (4) citizens from high human development countries other than France (HDI≥0.8). The same categorisation was applied to country of birth.

Figure 1 Spatial distribution of road traffic noise levels modelled across the city of Paris and spatial location of the 2130 participants of the RECORD Cohort Study.



Neighbourhoods were defined as census block groups (IRIS areas in France). These local units were designed by the French Census Bureau from the 1999 Census so as to have roughly comparable population sizes and to be relatively homogeneous in terms of socioeconomic and housing characteristics. The mean number of residents in the 571 neighbourhoods was 2507 in 1999 (range: 203–5555) and the mean number of participants per neighbourhood was 4 (range: 1–12).

The following socioeconomic variables were considered at the neighbourhood level: the proportion of residents aged 15 and over with an upper tertiary education (1999 Census), median income in 2005 (General Directorate of Taxation), mean value of dwellings sold in 2003–2007 (Paris-Notaries), the unemployment rate (1999 Census), the proportion of non-homeowners (1999 Census) and the proportion of overcrowded households (ie, households with more than one person per room; 1999 Census). We also considered variables related to the country of citizenship of residents defined at the TRIRIS area level for confidentiality reasons, that is, areas merging approximately three IRIS areas. First, we considered the proportion of non-French citizens. Then, using the same approach described for individual variables, we created for each TRIRIS area three additional variables based on the 1999 Census population data and 2004 HDI information: (1) the proportion of citizens from low human development countries; (2) the proportion of citizens from medium human development countries; and (3) the proportion of citizens from high human development countries other than France. Comparable variables were defined from the country of birth of residents (TRIRIS level). All neighbourhood variables were divided into four categories according to quartile cut-offs in the study population (ie, each category comprised a similar number of participants).

Statistical analysis

Associations between participants' exposure to road traffic noise and socioeconomic characteristics were estimated using different regression models. To derive parsimonious models, only individual/neighbourhood variables that were independently associated with noise levels were retained in the final models. To assess multicollinearity issues, Pearson's correlation coefficients between the selected neighbourhood variables are reported in online appendix 3.

Regression models

Model 1

First, we ran a standard linear regression model. This model ignores that observations are nested within neighbourhoods and considers that residual variability is reduced to an individual-level variability (σ_e^2).

$$Y_{ij} = \beta_0 + \beta X_{ij} + \beta' X'_j + e_{ij}$$

$$e_{ij} \sim Normal(0, \sigma_e^2)$$

where Y_{ij} corresponds to residential exposure level to road traffic noise of participant i living in neighbourhood j, β_0 is the intercept, X_{ij} and X'_j are the vectors of individual- and neighbourhood-level explanatory variables with the corresponding vectors of fixed effect parameters β and β'. The residuals e_{ij} are assumed to follow a normal distribution of variance σ_e^2 and to be independently and identically distributed (iid).

Model 2

Second, we ran a standard multilevel linear regression model. Contrary to model 1, this model takes into account the data's hierarchical structure by disentangling the residual variability at the individual level (σ_e^2) and at the neighbourhood level (σ_u^2). This model specification corrects the standard errors of fixed effect parameters (β and β') for the non-independence of observations within neighbourhoods.

$$Y_{ij} = \beta_0 + \beta X_{ij} + \beta' X'_j + e_{ij} + u_j$$

$$e_{ij} \sim Normal(0, \sigma_e^2)$$

$$u_j \sim Normal(0, \sigma_u^2)$$

In this model the individual-level and neighbourhood-level random effects e_{ij} and u_j are assumed: (1) to follow a normal distribution of variance σ_e^2 and σ_u^2, respectively; (2) to be iid; and (3) to be independent of each other.

We also assessed spatial autocorrelation in noise levels by estimating the Moran's I statistic for the neighbourhood random effect u_j. In the absence of spatial autocorrelation, Moran's I statistic has a small negative expectation when applied to regression residuals.[26]

Model 3

Third, we ran a spatial multilevel linear regression model. This model, contrary to model 2, considers the spatial structure of neighbourhoods and controls for spatial autocorrelation.[18 19] To do so, the neighbourhood-level random effect s_j is assumed to follow an intrinsic Gaussian conditional autoregressive distribution in which the random effect of neighbourhood j has, conditional on its surrounding neighbourhoods $-j$, a Gaussian distribution with mean being the average of the random effects for the surrounding neighbourhoods.[27] As for model 2, a normal distribution of variance σ_e^2 was specified for the individual-level error term e_{ij}.

$$Y_{ij} = \beta_0 + \beta X_{ij} + \beta' X'_j + e_{ij} + s_j$$

$$e_{ij} \sim Normal\left(0, \sigma_e^2\right)$$

$$s_j | s_{-j} \sim Normal\left(\bar{s_j}, \sigma_s^2 / m_j\right)$$

where $\bar{s_j}$ is the mean of the s_j for the neighbourhoods bordering neighbourhood j (contiguity being used as the criterion of geographical proximity), m_j is the number of neighbours of neighbourhood j, and the variance parameter σ_s^2 controls for the conditional variability of the neighbourhood-level random effect s_j.

Bayesian modelling

All models were estimated using Markov Chain Monte Carlo methods in WinBUGS v 1.4.3 (MRC Biostatistics Unit, Cambridge, UK). All details of our estimation strategy are described in online appendix 4, and WinBUGS codes for models 2 and 3 are reported in online appendix 5. Models were compared using the deviance information criterion (DIC); the model with the lowest DIC has the best overall combination of goodness-of-fit to the data and model parsimony.[28]

RESULTS

Road traffic noise modelled across Paris showed a strong geographical pattern coinciding with the road network (figure 1). The highest noise levels (>75 dB(A)) were observed near the principal high-traffic arteries, whereas the lowest levels (<55 dB(A)) were found around quiet environments (eg, public green spaces, cemeteries) and near the local residential and secondary roads. Accordingly, participants' noise exposure also showed substantial variability, with individual levels ranging from 55.8 to 73.7 dB(A) (mean: 64.4 dB(A)). Neighbourhood socioeconomic variables that were independently associated with noise levels also displayed specific geographical variations (figure 2A–C). For example, neighbourhoods with the highest proportions of highly educated residents were concentrated in the south-western part of Paris, whereas the neighbourhoods with the lowest proportions were located in the north-eastern area (figure 2A).

Table 1 provides descriptive statistics of participants' exposure to road traffic noise according to the socioeconomic characteristics of their residential neighbourhood. As suggested by comparing figure 1 with figure 2A,B, exposure levels increased steadily with educational level and dwelling value. A comparable trend was observed with the proportion of non-French citizens, although it seemed less marked. Nevertheless, whatever the neighbourhood variable considered, the variability in noise exposure levels between the four categories was relatively moderate.

Multiple regression analysis confirmed these descriptive findings. After controlling for individual covariates, the standard linear regression model showed increased noise levels with higher educational level and dwelling value, suggesting a greater exposure in more advantaged neighbourhoods (table 2, column 1). However, this model also suggested a seemingly opposite finding with increasing noise levels when the proportion of non-French citizens increased. The latter association was consistent with the individual-level association showing a higher exposure for non-French participants compared to French participants.

The same patterns were observed with the standard multilevel regression model, except that 95% credible intervals (CI) of neighbourhood fixed effects were, as expected, strongly increased as a consequence of the correction of regression coefficients for the non-independence of observations within neighbourhoods (table 2, column 2). This model had a lower DIC than model 1 (10 237 vs 7771) despite the increase in model complexity (the effective number of parameters p_D sharply increased from 13 to 513). After adjustment for individual- and neighbourhood-level explanatory variables, a very strong residual within-neighbourhood correlation remained in the data, as shown by the between-neighbourhood variance σ_u^2 (that only decreased from 6.35 (95% CI 5.57 to 7.21) to 5.54 (95% CI 4.85 to 6.32) between a model without explanatory variables and model 2). A substantial spatial autocorrelation also persisted in the neighbourhood residuals (Moran's I=0.45 (95% CI 0.41 to 0.48)), suggesting that a spatial multilevel regression model should be fitted to control for this phenomenon.[18 19]

However, in model 3, neighbourhood fixed effects were strongly affected; all associations previously identified totally disappeared (table 2, column 3). Adding a spatially structured neighbourhood random effect did not, as expected, merely correct the standard errors of regression coefficients for spatial autocorrelation but, on the contrary, completely perturbed neighbourhood fixed effects. This model had a lower DIC than model 2 (7772 vs 7696), as a result of a lower complexity rather than a better fit (the effective number of parameters p_D decreased from 513 to 456, while the posterior mean deviance $\bar{D}$ was only reduced from 7259 to 7240). Such disturbance of estimated fixed effects after adding spatial effects has been previously discussed in the biostatistical literature.[29 30] This can be explained by problems of collinearity between the neighbourhood explanatory variables and the spatial effects. This is especially problematic when explanatory variables have strong spatial patterns, as shown in figure 2. In this case, variability in the response can be explained by either the known explanatory variables or the spatial neighbourhood effects, leading to identifiability problems.[30] We found a positive correlation between each of the socioeconomic variables and the estimated neighbourhood-level random effects in the spatial multilevel model (see online appendix 6).

One way to sidestep these concerns was proposed by Reich *et al*[30] in the field of spatial epidemiology from disease-mapping models. Briefly, their approach consists of forcing the fixed and random components of the model to be independent by restricting the spatial random effect to the orthogonal complement of the fixed effects. We adapted this restricted spatial

Figure 2 Spatial distribution of neighbourhood socioeconomic variables across the city of Paris: proportion of highly educated residents (A), mean value of dwellings (B) and proportion of non-French citizens (C).

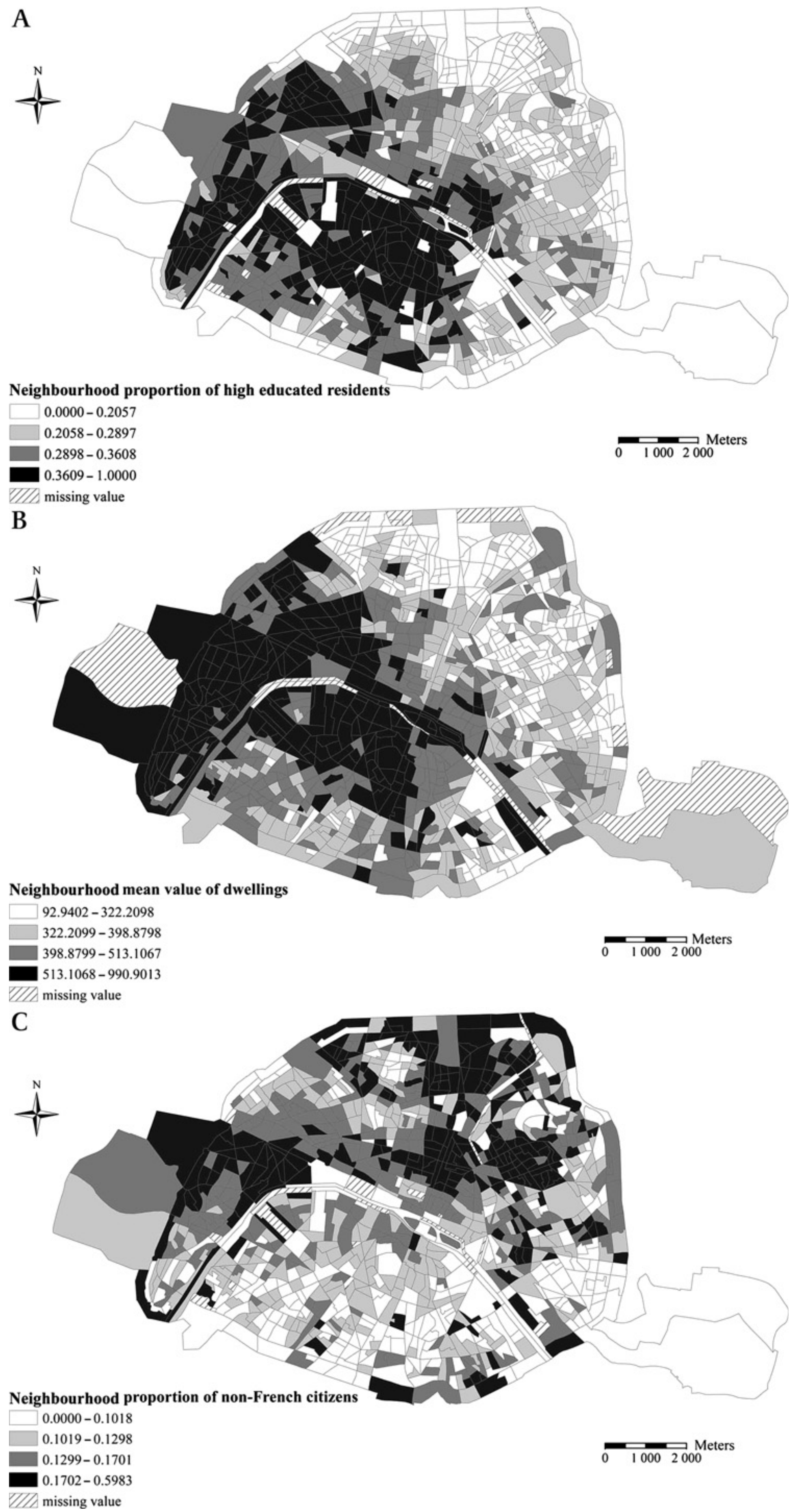


Table 1 Descriptive statistics of the distribution of study participants' exposure levels to road traffic noise (in dB(A)) according to neighbourhood socioeconomic characteristics, RECORD Cohort Study, Paris, France (n=2130)

	Mean	SD	Min	1st Quartile	Median	3rd Quartile	Max	p For trend*
Neighbourhood proportion of highly educated residents								
Low	63.9	2.9	57.3	62.0	63.5	65.5	73.7	<0.001
Mid-low	63.9	3.0	57.1	62.0	63.7	65.8	72.4	
Mid-high	64.6	2.7	57.5	62.8	64.6	66.4	71.7	
High	65.1	2.5	55.8	63.3	65.2	66.9	73.1	
Neighbourhood mean value of dwellings								
Low	63.9	2.7	57.3	62.1	63.9	65.7	73.7	<0.001
Mid-low	64.0	2.8	57.8	62.1	63.8	65.9	71.7	
Mid-high	64.5	2.5	57.1	62.8	64.4	66.3	71.7	
High	65.1	3.1	55.8	63.0	65.2	67.3	73.1	
Neighbourhood proportion of non-French citizens								
Low	63.7	2.9	55.8	61.7	63.4	65.3	72.4	<0.001
Mid-low	64.2	2.6	57.5	62.7	64.2	65.9	69.4	
Mid-high	65.0	3.1	57.8	62.8	64.9	67.4	73.1	
High	64.7	2.9	57.1	62.8	64.6	66.8	73.7	

*p Values for trend were estimated from the Jonckheere–Terpstra test. All neighbourhood variables were expressed as ordinal variables.
Max, maximum; Min, minimum. SD, standard deviation.

regression model, developed for aggregated data analysis, to our two-level dataset, and present the results in online appendix 7. As expected, the neighbourhood fixed effects previously observed were found. However, contrary to our expectations, the standard errors of regression coefficients did not increase but instead decreased compared to model 1 and model 2. Considering the inconsistent results found with this model and the spatial multilevel model, subsequent analyses were conducted using the standard multilevel model.

Given the conflicting associations observed with the different socioeconomic characteristics, it seemed relevant to distinguish the country of citizenship according to its HDI. Indeed, according to the human development level of the country of citizenship, the reasons for being in France may differ, and the social meaning of being a non-French citizen may not be the same. This specification yielded associations with noise levels that were substantially different from those previously identified (table 3). Participants' exposure independently increased with the proportion of citizens from high HDI countries in the neighbourhood, and decreased with increasing proportion of citizens from low HDI countries. These results were thus consistent with associations observed with other variables, suggesting a higher

Table 2 Regression analysis for the associations between study participants' residential exposure to road traffic noise and individual and neighbourhood socioeconomic characteristics, RECORD Cohort Study, Paris, France (n=2130)

	Model 1*		Model 2†		Model 3‡	
	β Coefficient§	(95% CI)	β Coefficient	(95% CI)	β Coefficient	(95% CI)
Individual country of citizenship (ref. French citizen)						
Non-French citizen	0.74	(0.36 to 1.12)	0.31	(0.09 to 0.54)	0.28	(0.06 to 0.50)
Neighbourhood proportion of highly educated residents (ref. Low)						
Mid-low	0.33	(−0.00 to 0.67)	0.27	(−0.31 to 0.85)	−0.24	(−0.69 to 0.21)
Mid-high	0.86	(0.51 to 1.21)	1.05	(0.41 to 1.68)	0.06	(−0.47 to 0.59)
High	1.16	(0.77 to 1.55)	1.20	(0.48 to 1.92)	0.22	(−0.44 to 0.87)
Neighbourhood mean value of dwellings (ref. Low)						
Mid-low	0.29	(−0.06 to 0.64)	0.24	(−0.37 to 0.85)	0.09	(−0.33 to 0.51)
Mid-high	1.05	(0.67 to 1.44)	0.94	(0.26 to 1.61)	0.42	(−0.09 to 0.91)
High	1.47	(1.07 to 1.88)	1.26	(0.52 to 2.00)	0.10	(−0.47 to 0.66)
Neighbourhood proportion of non-French citizens (ref. Low)						
Mid-low	0.56	(0.24 to 0.88)	0.75	(0.14 to 1.35)	0.11	(−0.45 to 0.68)
Mid-high	1.74	(1.40 to 2.08)	1.93	(1.32 to 2.55)	0.53	(−0.08 to 1.13)
High	1.99	(1.61 to 2.36)	2.15	(1.49 to 2.81)	0.35	(−0.36 to 1.07)
DIC	10 237		7772		7697	
p_D	13		513		456	
$\bar{D}$	10 224		7259		7241	

*Standard linear regression model.
†Standard multilevel linear regression model.
‡Spatial multilevel linear regression model.
§The β coefficient corresponds to the estimated regression coefficients.
CI, credible interval; $\bar{D}$, posterior mean deviance; DIC, deviance information criterion; p_D, effective number of parameters.

Table 3 Associations between study participants' residential exposure to road traffic noise and individual and neighbourhood socioeconomic characteristics (both individual and neighbourhood variables related to the country of citizenship were distinguished according to the countries' HDI), RECORD Cohort Study, Paris, France (n=2130)

	Model*	
	β Coefficient†	(95% CI)
Individual HDI of country of citizenship (ref. French HDI)		
Low HDI	0.49	(−0.13 to 1.10)
Medium HDI	0.32	(−0.02 to 0.66)
High HDI	0.27	(−0.02 to 0.57)
Neighbourhood proportion of highly educated residents (ref. Low)		
Mid-low	−0.28	(−0.86 to 0.32)
Mid-high	0.01	(−0.71 to 0.71)
High	−0.16	(−1.02 to 0.71)
Neighbourhood mean value of dwellings (ref. Low)		
Mid-low	0.13	(−0.45 to 0.71)
Mid-high	0.59	(−0.08 to 1.28)
High	0.87	(0.13 to 1.62)
Neighbourhood proportion of citizens from low HDI countries (ref. Low)		
Mid-low	−0.03	(−0.77 to 0.68)
Mid-high	−0.56	(−1.43 to 0.30)
High	−0.97	(−1.92 to −0.03)
Neighbourhood proportion of citizens from medium HDI countries (ref. Low)		
Mid-low	0.04	(−0.66 to 0.72)
Mid-high	1.20	(0.35 to 2.07)
High	1.35	(0.43 to 2.27)
Neighbourhood proportion of citizens from high HDI countries (ref. Low)		
Mid-low	0.30	(−0.29 to 0.87)
Mid-high	0.76	(0.16 to 1.35)
High	2.46	(1.78 to 3.13)
DIC	7773	
p_D	511	
$\bar{D}$	7262	

*Standard multilevel linear regression model.
†The β coefficient corresponds to the estimated regression coefficients.
CI, credible interval; $\bar{D}$, posterior mean deviance; DIC, deviance information criterion; HDI, Human Development Index; p_D, effective number of parameters.

exposure in socially advantaged than in disadvantaged neighbourhoods, although effects of educational level were completely explained by associations observed with HDI variables. At the individual level, the same conclusions could be drawn, with a greater exposure for participants from high HDI countries than French participants. These findings were also confirmed by comparing the spatial distribution of noise levels (figure 1) with spatial distributions of neighbourhood variables related to the countries' HDI (see online appendix 8).

DISCUSSION

This study demonstrates social inequalities in residential exposure to road traffic noise in Paris, France. However, contrary to most previous environmental justice studies, people living in socially advantaged neighbourhoods (in terms of education, dwelling value and country of citizenship) were likely to be exposed to higher noise levels than their deprived counterparts. Furthermore, the identified associations seemed highly sensitive to the definition of socioeconomic characteristics, especially for the citizenship status.

Compared to most previous studies that addressed environmental injustice in noise exposure,[11–14] our study is one of the few[15 16] that considered road traffic noise levels modelled in the local activity area around participants' residence, as the exposure estimate. Our exposure assessment was based on a validated model that integrated an extensive number of input parameters and showed a high precision in predicting noise levels. The meticulous geocoding of participants contributed to reducing exposure misclassification bias. However, this estimate was not intended to reflect the true individual measure of the overall noise exposure because it considers neither the time-activity patterns of individuals to account for exposures at home, the workplace and during transportation, nor other exposure sources such as neighbourhood noise, occupational noise, and other traffic-related noise sources such as aircraft and rail traffic. As these exposure components are also likely to vary between individuals and according to socioeconomic position, the associations identified in this study may not reflect the true associations between socioeconomic status and total noise exposure. However, road traffic noise is the dominating source of community noise in Paris and the primary source of noise-induced self-reported annoyance.[31]

Moreover, our original research design allowed exploration of social inequalities in noise exposure considering many individual and neighbourhood sociodemographic characteristics. To date, no study has taken into account such two-level information. Unfortunately, the mismatch in dates between the census data (1999) and the noise validity data (2007) may have diluted our associations. However, while absolute noise levels from road traffic may have increased since the last census, there is no reason to believe that their spatial distribution across Paris has changed substantially.

Following our recommendations,[18 19] we attempted to control for spatial autocorrelation. However, as previously discussed,[29 30] substantial collinearity between the explanatory variables and the spatial random effects may lead to identifiability problems in separating spatial residual from spatial covariate effects, resulting in severely biased and unreliable associations. We sought to sidestep this problem by adapting to our two-level dataset a recent biostatistical approach developed for aggregated data analysis, in which the spatial random effects are forced to be orthogonal to the fixed effects.[30] Unfortunately, contrary to what was expected, this model provided narrower credible intervals for the associations of interest that are difficult to explain given current knowledge and suggest further biostatistical research should be conducted in this field. Overall, our analysis may be a case study interesting to many epidemiologists, in that it shows that problems of collinearity between fixed and random model components may prevent effective control for spatial autocorrelation in certain cases, as previously recommended.[18 19]

Regarding empirical issues, our findings were consistent with the spatial organisation of the road network across Paris where noisier high-traffic arteries are mainly located in the vicinity of better-off business and tourist neighbourhoods. These latter are characterised by high proportions of educated residents, high housing values, high proportions of citizens from advantaged countries and low proportions of citizens from disadvantaged countries. Conversely, quieter neighbourhoods were predominantly located further away from the high-traffic roads and often had lower socioeconomic conditions.

Interestingly, we observed conflicting findings depending on how citizenship status was defined. When considering the proportion of non-French citizens, we concluded that there was higher noise exposure for people living in neighbourhoods with a large proportion of non-French citizens that were viewed as disadvantaged, a seemingly contrary finding to those found with educational level and dwelling value. But, when citizenship status was redefined according to the countries' HDI, we concluded that there was increasing noise exposure when the proportion of citizens from advantaged countries increased and the proportion of citizens from disadvantaged countries decreased, a finding consistent with those observed for the other socioeconomic variables. Moreover, initial analyses based on variables related to country of birth showed no associations with noise exposure levels once variables related to citizenship status were introduced in the regression models. These findings illustrate critical requirements for environmental justice studies: (1) caution regarding the interpretability and generalisability of preliminary results; and (2) systematic performance of rigorous sensitivity analyses using multiple socioeconomic characteristics so as to avoid drawing the wrong conclusions regarding the presence or absence of an environmental injustice situation.

Various mechanisms may explain exposure differentials among social groups and ethnic communities.[32] In our study, the unexpected findings may be attributable to historical, political, economic or social processes related to: (1) the historical context of Paris' urban development; (2) housing market dynamics; and (3) local and specific distribution of social classes across neighbourhoods. Due to their financial resources, affluent populations may choose to live in city centres where accessibility to workplaces, cultural activities, commercial services and other amenities is better and where the most famous and largest road arteries are located, rather than to live in quieter environments likely to be less attractive and less centrally located. Citizens from advantaged countries may also favour downtown neighbourhoods for professional reasons since business activities are generally concentrated in these areas. These specific circumstances may generate an increase in housing values and the subsequent migration of low-income groups towards low-cost housing areas where they can afford to live. In other neighbourhoods, the concentration of citizens from disadvantaged countries may be attributable to financial constraint as well as to cultural or ethnic preferences. All these hypotheses may explain why the proportions of residents from both advantaged and disadvantaged countries were particularly good markers of noise exposure.

Although well-off populations were more residentially exposed to road traffic noise, it should be noted that they are likely to perceive less noise-induced annoyance than their deprived counterparts,[31] because they can afford to protect themselves by equipping their dwelling with sound proofing including double- or triple-glazed windows.

Our results cannot be generalised to other territories with different urban dynamics, historical urban development patterns, land use planning policies and specific social make-up. We might have drawn different conclusions if our analysis had focused on the entire Paris metropolitan area rather than just on the city of Paris itself (noise data were not available for this broader area). Furthermore, the cross-sectional design does not allow determination of the chronology of causal mechanisms related to these inequalities, a concern that could be addressed through a longitudinal study.

In conclusion, contrary to most previous evidence of environmental injustice, our study supports the hypothesis that socially advantaged populations may be the most exposed to road traffic noise in their residential environment in Paris. Such differential exposure might generate unequal health effects between socioeconomic groups and ethnic communities.[10] Among the other major environmental hazards traffic-related air pollution may also be unevenly distributed among social classes[18 20] and may disproportionately affect the health of certain populations.[33] As these environmental risks may be jointly[5–7] and independently[34–38] associated with adverse health effects, especially cardiovascular endpoints, future socio-epidemiological studies should take into account their cumulative exposure as a potential explanatory mechanism for social gradient in health.[39]

Acknowledgements We are particularly grateful to Jim Hodges of the Division of Biostatistics, University of Minnesota for his comments and advice. We would like to express our gratitude to the institutions that provided financial support for the RECORD project. We particularly thank Sébastien Emery from the Department of Urban Ecology of the City of Paris for allowing us to access the data on road traffic noise levels modelled throughout Paris. We are also grateful to INSEE, the French National Institute of Statistics and Economic Studies, which provided support for the geocoding of the RECORD participants and allowed us to access relevant geographical data (with special thanks to Pascale Breuil and Jean-Luc Lipatz). We thank Geoconcept for giving us access to the Universal Geocoder software. Regarding the other geographical data used in the present analysis, we are also grateful to Paris-Notaries, the General Directorate of Taxation, the National Geographic Institute and the Institute of Planning and Urbanism from the Paris Region. We also thank the Caisse Nationale d'Assurance Maladie des Travailleurs Salariés (CNAM-TS, France) and the Caisse Primaire d'Assurance Maladie de Paris (CPAM-P, France) for helping make this study possible.

Funding Sabrina Havard is supported by a postdoctoral grant from the Health, Environment and Toxicology Ile-de-France Research Network (DIM SEnt) (Health, Environment and Toxicology Program 2008 CP-08-1062). As part of the RECORD project, the present work was also funded by the National Research Agency (Agence Nationale de la Recherche) (Health—Environment Program 2005 #00153 05), the Institute for Public Health Research (Institut de Recherche en Santé Publique), the National Institute for Prevention and Health Education (Institut National de Prévention et d'Education pour la Santé) (Prevention Program 2007 074/07-DAS), the National Institute of Public Health Surveillance (Institut de Veille Sanitaire) (Territory and Health Program), the French Ministries of Research and Health (Epidemiologic Cohorts Grant 2008), the National Health Insurance Office for Salaried Workers (Caisse Nationale d'Assurance Maladie des Travailleurs Salariés), the Ile-de-France Health and Social Affairs Regional Direction (Direction Régionale des Affaires Sanitaires et Sociales d'Île-de-France), the Ile-de-France Public Health Regional Group (Groupement Régional de Santé Publique), the City of Paris (Ville de Paris) and the Ile-de-France Youth and Sports Regional Direction (Direction Régionale de la Jeunesse et des Sports).

Competing interests None.

Ethics approval This study was conducted with the approval of the French Data Protection Authority.

Provenance and peer review Not commissioned; externally peer reviewed.

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