Small-area analysis of social inequalities in residential exposure to road traffic noise in Marseilles, France

Aurélie Bocquier, Sébastien Cortaredona, C Boutin, Aude David, Alexis Bigot, Basile Chaix, Jean Gaudart, Pierre Verger

Available at: http://www.nice.org.uk/nicemedia/live/11926/39557/39557.pdf (18 October 2011, date last accessed).

37 Cutler DM, Lleras-Muney A. Understanding differences in health behaviors by education. *J Health Econ* 2010;29:1–28.

38 Wilkie R, Peat G, Thomas E, Croft P. Factors associated with participation restriction in community-dwelling adults aged 50 years and over. *Qual Life Res* 2007;16:1147–56.

39 Ebrahim S, Papacosta O, Wannamethee G, Adamson J. Social inequalities and disability in older men: prospective findings from the British regional heart study. *Soc Sci Med* 2004;59:2109–20.

40 Jones MA, Stratton G, Reilly T, Unnithan VB. A school-based survey of recurrent non-specific low-back pain prevalence and consequences in children. *Health Educ Res* 2004;19:284–9.

European Journal of Public Health, Vol. 23, No. 4, 540–546

doi:10.1093/eurpub/cks059 Advance Access published on 29 May 2012

Small-area analysis of social inequalities in residential exposure to road traffic noise in Marseilles, France

Aurélie Bocquier[1,2,3], Sébastien Cortaredona[1,2,3], Céline Boutin[4], Aude David[4], Alexis Bigot[4], Basile Chaix[5,6], Jean Gaudart[7], Pierre Verger[1,2,3]

1 ORS PACA, Southeastern Health Regional Observatory, Marseille, France
2 INSERM, U912 ''Economic & Social Sciences, Health Systems & Societies'' (SE4S), Marseille, France
3 Université Aix Marseille, IRD, UMR-S912, Marseille, France
4 Soldata Acoustic, Villeurbanne, France
5 Inserm U707, Research Unit in Epidemiology, Information Systems, and Modelling, Paris, France
6 Université Pierre et Marie Curie—Paris 6, UMR-S 707, Paris, France
7 Aix-Marseille Univ, LERTIM EA3283, 13005, Marseille, France

Correspondence: Aurélie Bocquier, Observatoire régional de la santé Provence-Alpes-Côte d'Azur, 23 rue Stanislas Torrents, 13006 Marseille, France, tel: +33 (4) 91 59 89 09, fax: +33 (4) 91 59 89 18, e-mail: aurelie.bocquier@inserm.fr

Background: Few studies have focused on the social inequalities associated with environmental noise despite its significant potential health effects. This study analysed the associations between area socio-economic status (SES) and potential residential exposure to road traffic noise at a small-area level in Marseilles, second largest city in France. **Methods:** We calculated two potential road noise exposure indicators (PNEI) at the census block level (for 24-h and night periods), with the noise propagation prediction model CadnaA. We built a deprivation index from census data to estimate SES at the census block level. Locally estimated scatterplot smoothing diagrams described the associations between this index and PNEIs. Since the extent to which coefficient values vary between standard regression models and spatial methods are sensitive to the specific spatial model, we analysed these associations further with various regression models controlling for spatial autocorrelation and conducted sensitivity analyses with different spatial weight matrices. **Results:** We observed a non-linear relation between the PNEIs and the deprivation index: exposure levels were highest in the intermediate categories. All the spatial models led to a better fit and more or less pronounced reductions of the regression coefficients; the shape of the relations nonetheless remained the same. **Conclusion:** Finding the highest noise exposure in midlevel deprivation areas was unexpected, given the general literature on environmental inequalities. It highlights the need to study the diversity of the patterns of environmental inequalities across various economic, social and cultural contexts. Comparative studies of environmental inequalities are needed, between regions and countries, for noise and other pollutants.

Introduction

Noise imposes the second largest environmental burden on health, after ambient air pollution.[1] Relatively few studies examine inequalities in environmental noise exposure (from transportation, industrial or domestic sources), compared with the abundant literature about exposure to other environmental risks and pollutants (e.g. proximity to industrial and toxic waste sites or air pollution from industry and transportation).[2,3] The evidence is conflicting. Several studies show that individuals of low socio-economic status (SES)[2,4–6] or living in deprived areas[7,8] are more likely than others to report noise annoyance. Similarly, studies based on noise exposure modelling or indicators of proximity to noise sources (roads, railways and airports) report greater noise exposure among people of low SES[2,9–11] or belonging to specific communities (black ethnic groups).[12] Nonetheless, studies in the Netherlands and France report that environmental noise exposure levels are highest in advantaged neighbourhoods.[9,10,13]

Among these studies, only one attempted to take spatial autocorrelation (referred to hereafter as autocorrelation) into account[13] as recommended for studying environmental inequalities.[14,15] It refers to the non-independence of observations of neighbouring geographical areas.[16] More intuitively, spatial autocorrelation can be loosely defined as the coincidence of value similarity with locational similarity. Failure to take autocorrelation into account violates the hypotheses of independence that underlie the application of ordinary least square regression models and increases the risk of false-positive findings (type I error).[17]

Correction for autocorrelation might modify the relative size of regression coefficients corresponding to explanatory variables and their categories[17–19] differently, depending on the specific spatial model used. It follows that instead of using just one model that takes autocorrelation into account, as in the only study on noise inequalities that attempted to address this issue,[16] several different models should be compared.[17]

We conducted an ecological geographical study at a small-area level to test the hypothesis of an inverse relation between road noise exposure and deprivation at the small-area level in Marseilles (southeastern France) while taking autocorrelation into account. To verify the robustness of our results, we conducted our analyses with various statistical models and spatial weight matrices, as recommended for studying autocorrelation.[17,20]

Methods

Study area and spatial scale

Marseilles (852 395 inhabitants in 2007; 240.62 km^2) is second only to Paris in size among French cities. The spatial scale of the units of analysis was the French census block level, a submunicipal division designed by the National Institute for Statistics and Economic Studies (INSEE). It is the smallest geographic unit in France for which demographic and socio-economic information is available from the national census.[21] Marseilles comprises 392 census blocks; 54 with fewer than 250 inhabitants each in 2006 (2.9% of the total population) were excluded because INSEE reports reliability problems for the corresponding population census data. The average number of inhabitants in the remaining 338 census blocks was 2412 (minimum = 733; median = 2323; maximum = 4728).

Deprivation index

We built a socio-economic deprivation index at the census block level following a previously published method.[22] Briefly, we extracted 17 socio-economic and demographic variables that reflect various dimensions of deprivation (See Supplementary table 1) from the 2006 national population census (INSEE) for all the census blocks in Marseilles and conducted a principal component analysis. We defined the socio-economic deprivation index as the linear combination of the variables on the first axis of the analysis. We then divided this index according to quintiles: the first category, C_1, comprised the wealthiest census blocks, and the fifth, C_5, the most deprived.

Residential noise exposure assessment

Annual road traffic noise levels were modelled across Marseilles in 2006 as required by the Environmental Noise Directive (END) 2002/49/EC, by Soldata Acoustic, an agency specialized in noise mapping in France. It used the environmental noise prediction model CadnaA (Datakustik, Munich, Germany, version 4.0) to calculate acoustic propagation and noise levels in three-dimension. Noise calculations applied the following data: annual average daily traffic, including information on traffic intensity, composition, type and speed limits. Traffic information was available from the various transport authorities in Marseilles (for 2006). Other important input parameters include as follows: (i) propagation characteristics; (ii) geometry of buildings and roads; (iii) type of road surface; (iv) location of noise barriers; (v) topography; and (vi) meteorological factors. These data were obtained from the Marseilles municipal Directorate of Roads, the National Geographic Institute and other transport authorities. Those attributes are described in the European Commission Working Group Assessment of exposure to noise (WG-AEN) guidelines (Work Group for the END) and in the French guidelines edited by the CERTU.[23] The model used all these data to estimate noise levels at 4 m above the ground, as required by the END, at a 10 × 10 -m resolution. The noise level of each building was also calculated by energy-averaging noise levels at each facade of the relevant building.

The END specifies *L*den (day–evening–night level) and *L*n (night level) as the European standard indicators for assessing annoyance and sleep disturbance. The *L*den is defined as the A-weighted equivalent continuous noise level (LAeq) over a 24-h period in which levels during the evening (18:00–22:00) and night (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 take into account the physical sensitivity of human hearings at different sound frequencies. The *L*n is defined as the A-weighted equivalent continuous noise level (LAeq) during the night only.

We calculated an average indicator of potential road noise exposure (road PNEI) for the population residing in each census block;[24] the term potential is intended to clarify that the indicator does not evaluate true individual exposure. The noise level of each building calculated by CadnaA was then weighted by its estimated population. Finally, the data were compiled at the census-block scale to calculate the road PNEI with this formula:

$$\text{Road PNEI\_}L\text{den} = 10\times\log\left(\frac{1}{\text{ninhab}_{\text{tot}}}\sum\nolimits_{\text{build}}^{N}\text{ninhab}_{\text{build}}\times 10\left(\frac{L\text{den}_{\text{build}}}{10}\right)\right)$$

where $\text{ninhab}_{\text{tot}}$ is the number of inhabitants in the census block; N is the number of residential buildings (build) in the census block; $\text{ninhab}_{\text{build}}$ is the number of inhabitants of each residential building; and $L\text{den}_{\text{build}}$ is the (energy-averaged) noise level (*L*den) for each building.

The formula had the same structure for night time (road PNEI_*L*n) but used the *L*n instead of *L*den.

Statistical analysis

We used Spearman rank correlations and scatter plots with a smooth curve fitted by locally estimated scatterplot smoothing to describe bivariate associations between each PNEI and the deprivation index. We used Moran's index (I) to assess the autocorrelation for each road PNEI and for the deprivation index. Moran's index varies from −1 (negative autocorrelation, meaning that neighbouring census blocks have dissimilar values for the variable considered) to +1 (positive autocorrelation: similar values).

We first studied associations between each road PNEI (dependent variable) and the deprivation index (explanatory variable) with an ordinary least squares (OLS) regression model:

$$Y = X\beta + \varepsilon;\ \text{with}\ \varepsilon \sim \text{Normal}\left(0,\sigma^2\right)$$

where Y corresponds to the road PNEI, X to the deprivation index and β to the regression coefficient associated with the deprivation index.

To take autocorrelation into account in the case of lattice data (e.g. the lattice formed by the census blocks of Marseilles), we used two common types of autoregressive models: simultaneous autoregressive models (SARs)[25,26] and conditional autoregressive models (CARs).[27] The SAR models link the value of the variable Y in the ith area (Y_i) to a linear function of the values of Y in nearby areas;[20,27] for CAR models, it is the conditional expectation of Y_i with respect to all other values of Y that is defined as a linear function of the values of Y in nearby areas.[27] Specifically, we used two popular SAR models and one CAR model (See Supplementary Data, figure 1, for further details): the SAR_{lag} model, including the response variable as a covariate in the form of a spatially lagged variable; the SAR_{err} model, including a spatial error structure to control for autocorrelation;[25,26] and the intrinsic conditional autoregressive (ICAR) model, which is a generalization of the standard CAR model to support an irregular lattice (that formed by the census blocks of Marseilles).[28,29]

We compared these four models (OLS, SAR_{lag}, SAR_{err} and ICAR) with the Akaike information criterion (AIC, which evaluates a

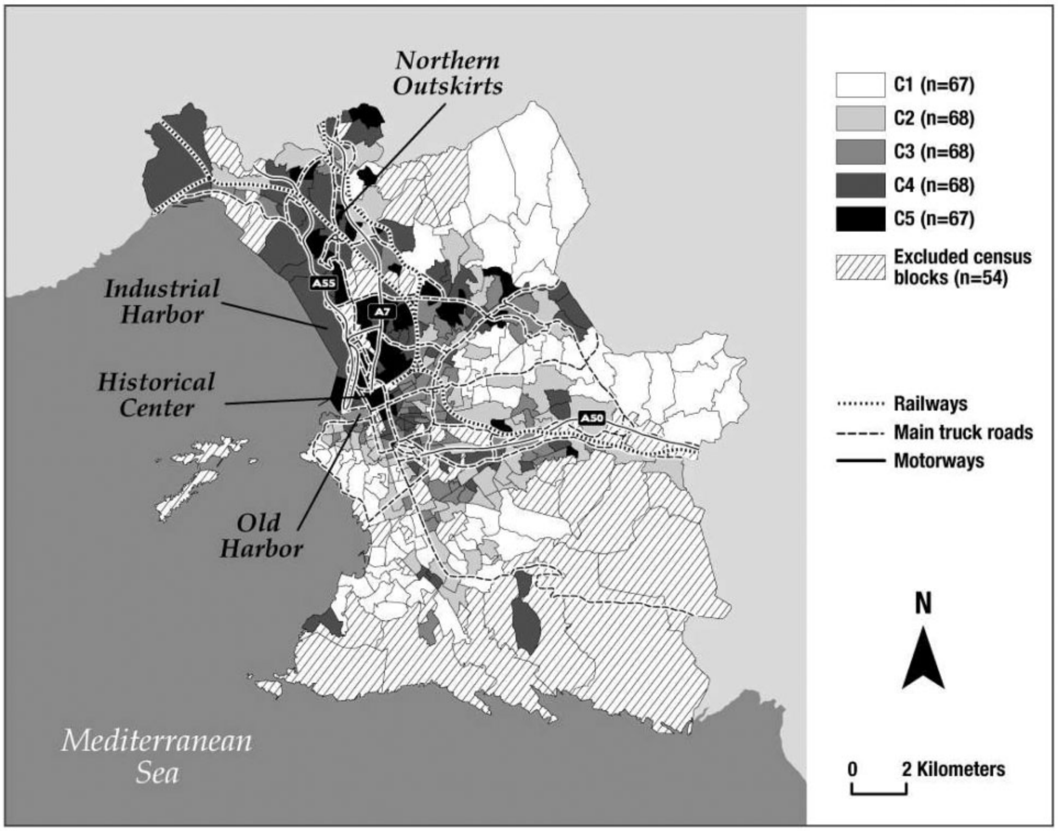

Figure 1 Spatial distribution of the deprivation index (C_1 is the least deprived category) in the city of Marseilles (France) at a small-area level ($n = 338$ census blocks)

combination of goodness of fit and complexity) and residual autocorrelation. To better understand why the estimates of the regression coefficients shifted substantially between the spatial models and standard OLS, we calculated Spearman rank correlations between the spatially correlated errors of the models and the deprivation index, as suggested when the explanatory variable shows significant autocorrelation[13] (See Supplementary Data, figures 1 and 2 for further details).

To assess the influence of the choice of the spatial weight matrix W on the models' goodness of fit and regression coefficient estimates, we performed a sensitivity analysis with six matrices that used various criteria to define the neighbours of each census block (See Supplementary Data for their definitions). Finally, given the unequal population size of the census blocks, we performed population-weighted models for the OLS and ICAR models, which had minimal effect on our results (results available from the author on request).

Analyses were performed with SAS version 9.2 (SAS Institute, Cary, NC, USA) and GeoDa version 0.9.5-i. (Spatial Analysis Laboratory, University of Illinois, Urbana-Champaign, IL, USA). ICAR modelling was performed with the SAS code provided by Rasmussen.[29]

Results

The deprivation index (figure 1) showed a strong positive autocorrelation ($I = 0.42$), as did the road PNEIs ($I = 0.45$ for *L*den and 0.53 for *L*n) (see figure 2 for PNEI_ *L*den and Supplementary Data, figure 3 for PNEI_*L*n).

Spearman correlations between the deprivation index and the road PNEIs were positive and significant (for *L*den and *L*n, respectively: $\rho = 0.31$; $P < 0.0001$ and $\rho = 0.32$; $P < 0.0001$). The scatterplot of the road PNEI_ *L*den according to the deprivation index showed substantial dispersion of the former, which tended to increase with deprivation (figure 3). The mean road PNEI_ *L*den was highest for the intermediate categories of the deprivation index (C_3 and C_4, table 1). Similar results were observed for the road PNEI_*L*n (see Supplementary figure S4 and Supplementary table S2).

The OLS model showed that the road PNEI_*L*den was non-linearly associated with the deprivation index: it increased with deprivation from the first to the third deprivation categories and tended to decrease from the third to the fifth categories (table 1). Positive autocorrelation in the residuals of this model ($I = 0.33$) justified the use of spatial models.

Regardless of the spatial model used, taking autocorrelation into account improved the model fit (lower AIC and residual autocorrelation) and reduced the coefficients, most notably in the SAR_{err} model (table 1). Nonetheless, the coefficients remained positive and associated with increased exposure for the C_2–C_4 categories of the deprivation index in the SAR_{lag} and ICAR models and for the C_2 and C_3 categories in the SAR_{err} model. As with the OLS model, the shape of the relation was non-linear in all three spatial models. The stronger the correlation between the spatial errors and the deprivation index, the greater the change in the regression coefficients for deprivation compared with the OLS model (see Supplementary Data, figure 2). The sensitivity analyses indicated that regression coefficients related to the C_2–C_4 categories were most often positively associated with exposure (see Supplementary table S3 and Supplementary figure S5). We observed similar results for the road PNEI_*L*n (see Supplementary table S2).

Discussion

We observed a non-linear relation between the road PNEIs and the deprivation index at the census-block level in Marseilles: noise exposure levels were highest in the intermediate categories of this

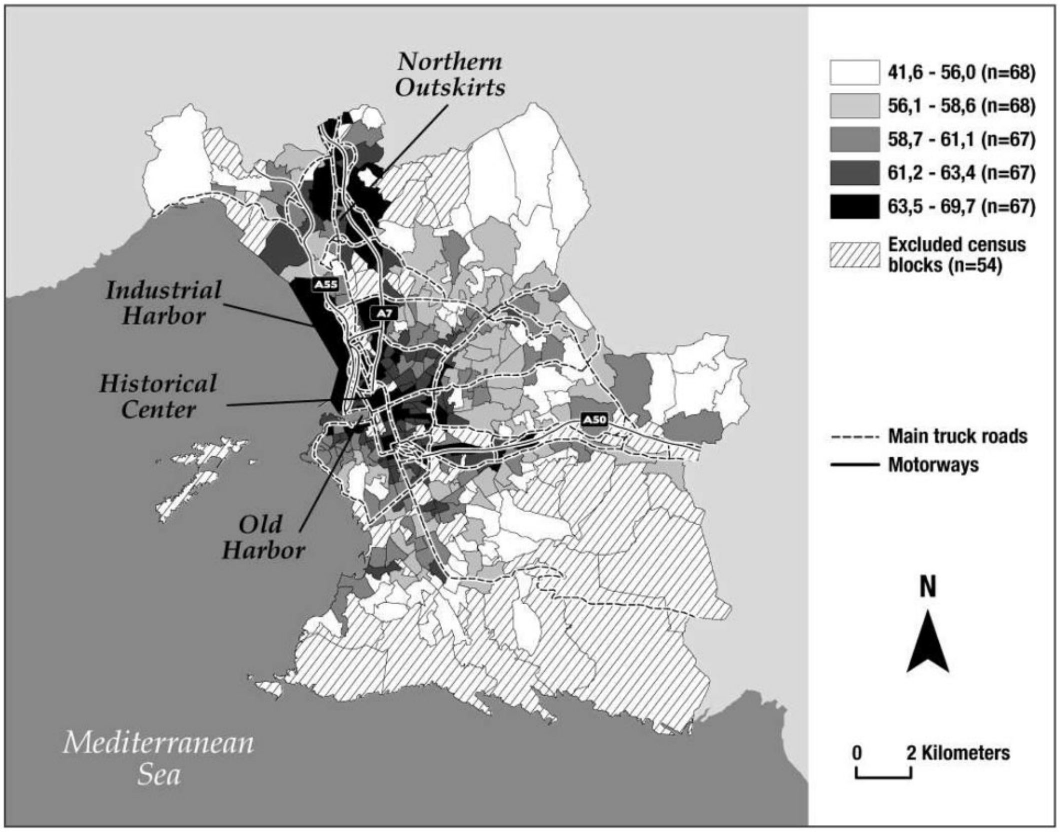

Figure 2 Spatial distribution of the road potential noise exposure indicator *L*den [dB(A)] in Marseilles (France) at a small-area level ($n = 338$ census blocks)

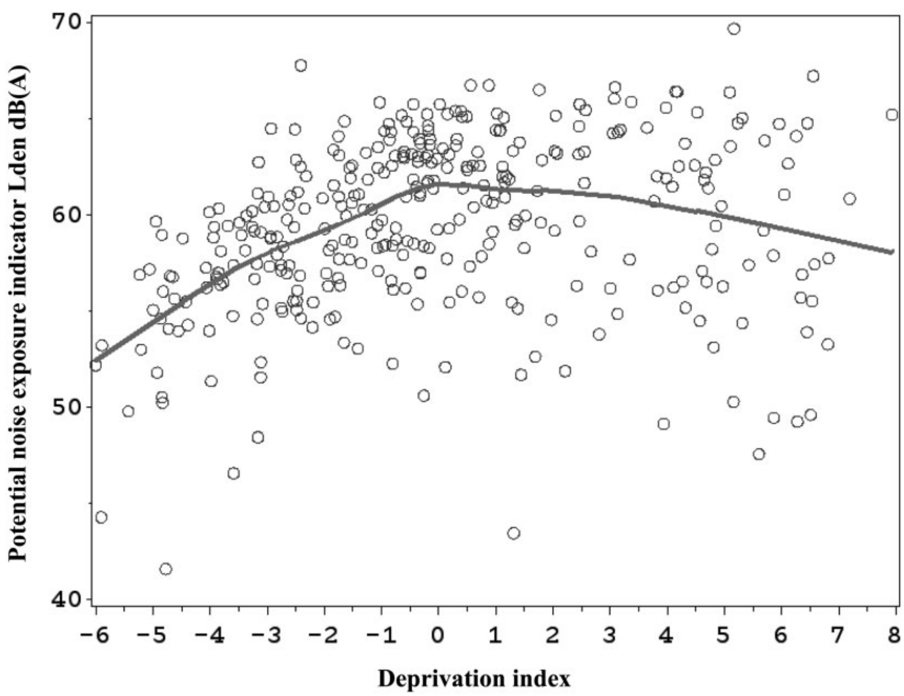

Figure 3 Locally estimated scatterplot smoothing plot of the association between the road potential noise exposure indicator *L*den [dB(A)] and the deprivation index (highest values correspond to highest levels of deprivation) at a small-area level in Marseilles (France, $n = 338$ census blocks)

index. Both the PNEIs and the deprivation index had significant and positive autocorrelation. All the models taking autocorrelation into account produced better fit and lower estimated coefficients than the standard regression. Some of these spatial models did not find significant differences in exposure between census blocks ranked in the lowest (C_1) and the highest (C_5) deprivation categories. However, the shapes of the relations remained the same, regardless of the model and spatial matrix used.

Table 1 Association between the road potential noise exposure indicator *L*den [dB(A)] and the deprivation index with different statistical models[a] (Marseilles city, France, $n = 338$ census blocks)

		Mean (SD)	OLS		SAR_{lag}		SAR_{err}		ICAR	
			β (SD)[b]	*P*-value	β (SD)[b]	*P*-value	β (SD)[b]	*P*-value	β (SD)[b]	*P*-value
	Intercept		56.17 (0.51)	<0.0001	23.56 (2.66)	<0.0001	42.21 (3.04)	<0.0001	57.98 (0.42)	<0.0001
Deprivation categories	C_1[c]	56.2 (4.2)	0.00	Ref.	0.00	Ref.	0.00	Ref.	0.00	Ref.
	C_2	59.2 (3.2)	**3.00 (0.71)**	**0.0003**	**2.00 (0.59)**	**0.0006**	**1.38 (0.58)**	**0.0172**	**1.84 (0.56)**	**0.0011**
	C_3	61.2 (3.5)	**5.00 (0.71)**	**<0.0001**	**3.16 (0.59)**	**<0.0001**	**1.76 (0.66)**	**0.0072**	**3.00 (0.61)**	**<0.0001**
	C_4	60.8 (4.3)	**4.62 (0.71)**	**<0.0001**	**3.10 (0.59)**	**<0.0001**	1.03 (0.67)	0.1271	**2.19 (0.63)**	**0.0006**
	C_5	59.9 (5.3)	**3.75 (0.72)**	**<0.0001**	**1.31 (0.59)**	**0.0268**	**−1.63 (0.76)**	**0.0304**	0.32 (0.78)	0.6459
	λ[d]				0.54 (0.05)	<0.0001				
	ρ[d]						0.99(0.00)	<0.0001		
	AIC[e]		1926		1800		1734		1764	
	I[f] residual		0.33		0.09		−0.06		−0.05	

a: Weight matrix is a cumulative second-order rook contiguity matrix of all models. See Supplementary Data for a detailed presentation of the matrices

b: Regression coefficient (standard error)

c: C_1 is the least deprived category and was taken as a reference

d: Spatial autoregressive parameters

e: Akaike information criterion

f: Moran's index

Bold values: statistical significant associations ($p < 0.05$)

Limitations and strengths

These findings should be interpreted cautiously and with the following methodological considerations borne in mind. First, our study was ecological. We did not collect individual data about social characteristics, noise exposure, living conditions or residential characteristics; social disparities exist in the measures individuals can afford to take to protect their homes against environmental noise (e.g. double glazing or air conditioning to avoid opening windows in summer).[2] No inferences can thus be drawn from our results at the individual level.[30] Furthermore, the chronology of causal mechanisms related to the inequalities we observed cannot be determined from this cross-sectional design.

Secondly, road PNEIs were estimated with the CadnaA prediction model, a well-recognized tool for urban noise mapping.[31] It requires, however, large quantities of input data and parameters, each subject to some degree of uncertainty, due to data sources, estimation methods or measurement tools. Since all of these are difficult to assess and could not be taken into account in the modelling, they could have induced substantial exposure error.

Thirdly, one strength of this study is that it applied recommendations of recent advanced research in the field of geographical ecology[17,20] to address spatial autocorrelation. This is required to ensure the validity of the statistical models and reduce the risk of type I errors. This risk may be especially important in this study because the spread of noise levels within each census block was probably substantial. In the absence of individual data, addressing spatial autocorrelation was thus necessary and led to better model fit and lower residual autocorrelation (substantial reduction of AIC and Moran's index between OLS and spatial models, table 1). Regardless of the model, we observed a similar non-linear relation between the PNEI and deprivation index, with exposures highest in the intermediate deprivation categories. This finding demonstrates the stability of this result. However, the coefficients estimated for the deprivation effect might have been spuriously distorted, which could explain, for example, the lack of real differences in the PNEIs for the C_1 and C_5 categories in the ICAR model. Substantial collinearity existed between the explanatory variable (deprivation index) and the models' spatial error terms (see Supplementary Data, figures 1 and 2), as observed elsewhere.[13] This correlation might be due to the inability of the regression models to separate the spatial random effect from the deprivation effect when both the outcome and explanatory variables are strongly correlated.[13,32,33] Further research is needed to address this problem.[13]

Comparison with the published literature

Most studies based on noise exposure estimations or indicators of proximity to noise sources (roads, railways and airports) have reported greater noise exposure among people of low SES[2,9–11] or belonging to specific disadvantaged ethnic groups.[12] Our results, somewhat unexpected in light of the general literature on environmental inequalities, are nonetheless similar to those of several other studies in France and elsewhere in Europe. For example, the highest noise exposure levels from road traffic in Paris (France) were observed in advantaged neighbourhoods.[13] In the largest French region (Ile-de-France), advantaged and deprived areas do not differ in their exposure to noise from road traffic or small airports.[9] In a Dutch region, the highest levels of aircraft noise exposure were found in advantaged neighbourhoods,[10] and in Norway, the relation between individual SES and noise exposure varies according to the size of the city.[11] In the city of Strasbourg (eastern France), a study of environmental inequalities associated with air pollution found a non-linear relation between levels of air pollution and deprivation, with the greatest exposure in the intermediate census blocks.[26]

Hypotheses related to local history of urban planning

Common explanations of environmental inequalities include economic (e.g. housing market dynamics, income), socio-political (e.g. participation in decision making, capacity to mount effective opposition) and ethnic discrimination.[3] In particular, ethnic barriers and economic conditions probably play central roles in shaping the micro-level mobility dynamics underlying environmental inequalities.[34] Our results should be viewed in the context of local history, urban design and land-use planning. Together with economic, socio-political and ethnic factors, these might explain the pattern of environmental inequalities we found, different from that the bulk of the published literature led us to expect.

Marseilles, located on the Mediterranean coast, is one of the oldest cities in Europe (founded in 600 BC). Its historic centre is located on the north side of the Old Harbour and was home to most commercial and craft activities until the 19th century, when the industrial harbour was constructed on the northern coast. The city subsequently spread out around the Old Harbour into the surrounding countryside differentially according to social class: the upper middle classes settled in the south and east, fleeing the working class areas in the noisy city centre, while some of the working class moved to the north, where jobs opportunities increased. Urban planning during the 1950s through the 1970s accentuated this spatial distribution of social classes by constructing 90% of new subsidized (public) housing in the northern outskirts of the city.[35] This spatial distribution is still observed today, with the most deprived census blocks mainly located in two parts of the city: the northern part of the historic city centre (with high exposure to road traffic noise, old, partly dilapidated housing and housing prices lower than in the rest of the city), and the northern outskirts of Marseilles, where the road network is less dense than in the city centre. The substantial variability in road noise exposure in the C_5 category might have masked true differences between this category and C_1. Residents of the C_3 deprivation class (and to some extent those of the C_2 and C_4 categories) live along the principal state highways in the eastern part of Marseilles, in areas where housing is dense and road PNEIs are the highest. At the same time, they have access to lower housing costs than residents of more affluent census blocks, and better access to public transportation and fewer social disadvantages than those of areas located on the outskirts of the city.[35]

Our study, applying recently recommended methodological approaches for dealing with autocorrelation, found social inequalities in potential residential exposure to road traffic noise in Marseilles (France), with exposure highest in areas of intermediate deprivation. It highlights the need to study the diversity of the patterns of environmental inequalities across various economic, social and cultural settings and suggests that comparative studies of environmental inequalities are needed across regions and countries for noise and other pollutants. Further research is needed to improve our understanding of the process by which these inequalities are constructed and to help public authorities to design effective national and local policies to reduce them.

Supplementary data

Supplementary data are available at *EURPUB online*.

Funding

This study was conducted with the financial support of the Agence de l'environnement et de la maîtrise de l'énergie (Ademe) as part of its 2009 call for research projects in the field of the environment, health and work (convention n°0966C0272) and from the Groupement d'intérêt scientifique Institut de recherche en santé publique (GIS-IReSP) as part of their 2008 call for research projects in the field of territory and health.

Conflict of interest: None declared.

Key points

- Despite the significant potential health effects of environmental noise, few studies have focused on social inequalities in exposure to it, and the evidence appears conflicting.
- The only study that attempted to take spatial autocorrelation into account (as recommended for studying environmental inequalities) highlighted methodological difficulties and suggested that similar analyses be conducted in other settings with more advanced methods that would improve consideration of spatial autocorrelation.
- We assessed social inequalities in residential exposure to road traffic noise at a small-area level in Marseilles while taking spatial autocorrelation into account and testing the robustness of our results with various spatial statistical models and weight matrices (which has not been previously done).
- Regardless of the spatial model or matrix used, exposure levels were highest in the intermediate categories of deprivation; this robust finding, although similar to others in the field of noise, was nonetheless somewhat unexpected in light of the general literature on environmental inequalities.
- The results highlight the need for comparative studies of environmental inequalities across regions and countries.

References

1 World Health Organization. EBoDE-project on WHO ECEH web site. 2009. Available at: http://en.opasnet.org/w/EBoDE (11 October 2011, date last accessed).

2 Evans GW, Kantrowitz E. Socioeconomic status and health: the potential role of environmental risk exposure. *Annu Rev Public Health* 2002;23:303–31.

3 Mohai P, Pellow D, Roberts JT. Environmental Justice. *Annu Rev Environ Resour* 2009;34:405–30.

4 Constance J, Grénetier N, Peretti-Watel P. Bruit. In: Ménard C, Girard D, Léon C, Beck F, editors. *Baromètre Santé Environnement 2007*. Saint-Denis: Inpes, 2008: 327–46.

5 Kohlhuber M, Mielck A, Weiland SK, et al. Social inequality in perceived environmental exposures in relation to housing conditions in Germany. *Environ Res* 2006;101:246–55.

6 Poortinga W, Dunstan FD, Fone DL. Neighbourhood deprivation and self-rated health: the role of perceptions of the neighbourhood and of housing problems. *Health Place* 2008;14:562–75.

7 Champion JB, Choffel P, Dupont E, et al. Les nuisances et les risques environnementaux. In: Observatoire national des zones urbaines sensibles, editors. *Rapport 2004 de l'Observatoire National des zones urbaines sensibles*. Paris: Editions de la DIV, 2004: 125–31.

8 Le Jeannic T. On pardonne tout à son quartier sauf... l'insécurité, les dégradations, le bruit. *INSEE PREMIERE* 2007;1133:1–4.

9 Faburel G, Gueymard S. Inégalités environnementales en régions Ile-de-France : le rôle structurant des facteurs négatifs de l'environnement et des choix politiques afférents. *Espace populations sociétés* 2008;1:159–72.

10 Kruize H, Bouwman AA. Environmental (in)equity in the Netherlands. A case study on the distribution of environmental quality in the Rijnmond region; 2004. Report No.: 550012003/2004.

11 Fyhri A, Klaeboe R. Direct, indirect influences of income on road traffic noise annoyance. *J Environ Psychol* 2006;26:27–37.

12 Brainard JS, Jones AP, Bateman IJ, et al. Exposure to environmental urban noise pollution in Birmingham, UK. *Urban Stud* 2004;41:2581–600.

13 Havard S, Reich BJ, Bean K, et al. Social inequalities in residential exposure to road traffic noise: an environmental justice analysis based on the RECORD Cohort Study. *Occup Environ Med* 2011;68:366–74.

14 Briggs D, Abellan JJ, Fecht D. Environmental inequity in England: small area associations between socio-economic status and environmental pollution. *Soc Sci Med* 2008;67:1612–29.

15 Laurian L. The distribution of environmental risks. Analytical methods and French data. *Population* 2008;63:711–29.

16 Haynes KE, Lall SV, Trice MP. Spatial issues in environmental equity. *Int J Environ Tech Manag* 2001;1:17–31.

17 Bini LM, Diniz JAF, Rangel T, et al. Coefficient shifts in geographical ecology: an empirical evaluation of spatial and non-spatial regression. *Ecography* 2009;32: 193–204.

18 Lennon JJ. Red-shifts and red herrings in geographical ecology. *Ecography* 2000;23: 101–13.

19 Diniz JAF, Bini LM, Hawkins BA. Spatial autocorrelation and red herrings in geographical ecology. *Glob Ecol Biogeogr* 2003;12:53–64.

20 Kissling WD, Carl G. Spatial autocorrelation and the selection of simultaneous autoregressive models. *Glob Ecol Biogeogr* 2008;17:59–71.

21 INSEE. Bases de données infra-communales—IRIS. Documentation générale. 2007. Available at: http://www.recensement-2007.insee.fr/telechargement/documentation/doc_bases_infracommunales_2007.pdf (11 October 2011, date last accessed).

22 Havard S, Deguen S, Bodin J, et al. A small-area index of socioeconomic deprivation to capture health inequalities in France. *Soc Sci Med* 2008;67:2007–16.

23 Certu. Comment réaliser les cartes de bruit stratégiques en agglomération. *Mettre en oeuvre la directive 2002/49/CE*. Lyon: Certu, 2007.

24 International Organization for Standardization. ISO standard 9612, Acoustics—Determination of occupational noise exposure—Engineering method. Geneva: International Organization for Standardization, 2009.

25 Anselin L. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publisher, 1988.

26 Havard S, Deguen S, Zmirou-Navier D, et al. Traffic-related air pollution and socioeconomic status: a spatial autocorrelation study to assess environmental equity on a small-area scale. *Epidemiology* 2009;20:223–30.

27 Bell BS, Broemeling LD. A bayesian analysis for spatial processes with application to disease mapping. *Stat Med* 2000;19:957–74.

28 Besag J, York J, Mollié A. Bayesian image restoration, with two applications in spatial statistics. *Ann Institute Stat Mathematics* 1991;43:1–20.

29 Rasmussen S. Modelling of discrete spatial variation in epidemiology with SAS using GLIMMIX. *Comput Methods Programs Biomed* 2004;76:83–9.

30 Diez-Roux AV. Bringing context back into epidemiology: variables and fallacies in multilevel analysis. *Am J Public Health* 1998;88:216–22.

31 Fyhri A, Aasvang GM. Noise, sleep and poor health: modeling the relationship between road traffic noise and cardiovascular problems. *Sci Total Environ* 2010;408: 4935–42.

32 Reich BJ, Hodges JS, Zadnik V. Effects of residual smoothing on the posterior of the fixed effects in disease-mapping models. *Biometrics* 2006;62:1197–206.

33 Hodges JS, Reich BJ. Adding spatially-correlated errors can mess up the fixed effect you love. 2010. Available at: http://www.biostat.umn.edu/ftp/pub/2010/rr2010-002.pdf. (11 October 2011, date last accessed).

34 Crowder K, Downey L. Interneighborhood migration, race, and environmental hazards: modeling microlevel processes of environmental inequality. *Am J Sociol* 2010;115:1110–49.

35 Dell'Umbria A. Histoire universelle de Marseille. De l'an mil à l'an deux mille. Marseille: Agone. Mémoires socials, 2006.

European Journal of Public Health, Vol. 23, No. 4, 546–551

doi:10.1093/eurpub/cks083 Advance Access published on 17 June 2012

Using multiple measures of inequalities to study the time trends in social inequalities in smoking

Rana Charafeddine, Stefaan Demarest, Johan Van der Heyden, Jean Tafforeau, Herman Van Oyen

Unit of Public Health and Surveillance, Scientific Institute of Public Health, Belgium

Correspondence: Unit of Public Health and Surveillance, Scientific Institute of Public Health, 14, Juliette Wytsman street, 1050 Brussels, Belgium, tel: +32 2 642 5739, fax: +32 2 642 5001, e-mail: Rana.Charafeddine@wiv-isp.be

Background: The time trends in social inequalities in smoking have been examined in a number of international publications; however, these studies have rarely used multiple measures of health inequalities simultaneously. Also the analytical approach used often did not account, as recommended, for the changes in the relative distribution of social groups and the changes in the absolute level of the health outcome within social groups. **Methods:** Data from four successive waves of the Belgian Health Interview Survey (1997, 2001, 2004, 2008) were used to study the time trends in educational inequalities in daily smoking for those aged between 15 and 74 years. We estimated two measures of relative inequalities: the OR and the relative index of inequality; and two measures of absolute inequalities: the population attributable fraction and the slope index of inequality. Three of these measures (relative index of inequality, population attributable fraction, slope index of inequality) account for the change in the relative size of the social groups over time. **Results:** The four measures of inequality were consistent in showing significant inequalities among educational groups. The time trends, however, were less consistent. Measures of trends in relative inequalities witnessed a small linear increase. However, no substantial over time change was observed with the measures of absolute inequalities. **Conclusion:** The time trends in social inequalities in smoking varied according to the measure of inequality used. This study confirms the importance of using multiple measures of inequalities to understand and monitor social inequalities in smoking.

Introduction

It has been widely acknowledged in the literature that smoking and smoking-related diseases contribute substantially to health inequalities.[1–4] This has generated a keen interest among researchers and policy makers in monitoring the time trends in social inequalities in smoking. A non-systematic review of the literature was undertaken to identify the studies published since 2000 that examined the time trends in smoking by socio-economic status (SES) in European countries. As a result, 11 studies were found to examine the trends in social inequalities in smoking in adult populations [5–15] and five studies among subpopulations, namely adolescents and pregnant women [16–20] (a summary table is available as an online supplementary material). This review shows that in most European countries social inequalities in smoking are increasing or persisting over time. Also, it shows that most of these studies relied on one measure of inequality and had an analytical approach that did not account for the over time changes in the population. Two