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# Environmental noise is positively associated with socioeconomically less privileged neighborhoods in the Netherlands

Max Hayward [1], Marco Helbich [*,1]

*Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands*

A R T I C L E  I N F O

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A B S T R A C T

*Background:* Environmental noise has detrimental effects on various health outcomes. Although disparities in some environmental exposures (e.g., air pollution) are well-documented, there is still a limited and uncertain understanding of the extent to which specific populations are disproportionately burdened by noise.
*Aim:* To assess whether environmental noise levels are associated with demographic and socioeconomic neighborhood compositions.
*Methods:* We cross-sectionally examined long-term noise levels for 9,372 neighborhoods in the Netherlands. We linked these noise levels with administrative data on neighborhood characteristics for the year 2021. Linear and non-linear spatial regression models were fitted to explore the associations between noise, demographic, and socioeconomic neighborhood characteristics.
*Results:* Our results showed that 46 % of the neighborhoods exhibited noise levels surpassing the recommended threshold of 53 dB to prevent adverse health effects. The regressions uncovered positive and partially non-linear neighborhood-level associations between noise and non-Western migrants, employment rates, low-incomers, and address density. Conversely, we found negative associations with higher-educated neighborhoods and those with a greater proportion of younger residents. Neighborhoods with older populations displayed a U-shaped association.
*Conclusions:* This national study showed an inequality in the noise burden, adversely affecting vulnerable, marginalized, and less privileged neighborhoods. Addressing the uneven distribution of noise and its root causes is an urgent policy imperative for sustainable Dutch cities.

## 1. Introduction

Growing research assesses the role of environmental exposures as a contributing factor to health inequalities (Brulle and Pellow, 2006; Van Horne et al., 2023). The environmental injustice literature suggests that exposures tend to be unevenly distributed with higher environmental noise levels in urbanized areas (Liu, 2001; Stansfeld et al., 2000) and that marginalized residential neighborhoods face a disproportionately high burden (Mohai et al., 2009; Mohai and Saha, 2015). Studies revealed, for example, that the burden of air pollution (Hajat et al., 2015) and ambient light at night falls upon those most vulnerable, economically, and socially unprivileged (Nadybal et al., 2020). Likewise, meta-analyses substantiated that tree occurrences were tentatively related to race (Watkins and Gerrish, 2018) and more robustly associated with income (Gerrish and Watkins, 2018).

Environmental noise emitted from, for example, transport and rail, constitutes another environmental stressor detrimental to human health (Basner et al., 2014; Welch et al., 2023). Annual European estimates place the number of premature deaths caused by long-term noise at approximately 12,000 (European Environment Agency, 2019), with an associated yearly loss of one million healthy life years from traffic-related noise in Western Europe (World Health Organization, 2011). Several reviews and meta-analyses have suggested positive associations between traffic noise and, for example, depressive symptoms (van den Bosch and Meyer-Lindenberg, 2019), anxiety symptoms (Lan et al., 2020), and cardiovascular disease (Münzel et al., 2021).

Despite its adverse health effects, noise is less acknowledged as an environmental justice subject (Preisendörfer et al., 2022). Pooling the piecewise findings from two reviews, both on the ecological level and personal level, crystallizes that results are mixed with partly opposing

* Corresponding author.
*E-mail address:* m.helbich@uu.nl (M. Helbich).
[1] Both authors contributed equally.

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associations (Dreger et al., 2019; Trudeau et al., 2023). For example, traffic noise burdened those earning the least in Montreal (Canada) (Carrier et al., 2016) and those living in deprived areas in Marseilles (France) (Bocquier et al., 2013). In Berlin (Germany), however, disparities in noise were heterogeneous (Lakes et al., 2014), a trend that Barcelona (Spain) (Lagonigro et al., 2018) and London (UK) paralleled (Tonne et al., 2018). These results counter those from Paris (France), where those in advantaged neighborhoods faced higher traffic noise (Havard et al., 2011).

While insightful, the evidence on noise inequalities has limitations. First, the few European studies are often restricted in their analytical coverage, limiting the generalization of the findings. Dutch-related noise pollution research specifically, where it does exist, has only focused on single emission sources, like Schiphol airport (Kruize et al., 2007). Second, besides between-country health inequalities (Mackenbach et al., 2008), results on noise inequality assessments from North America (Casey et al., 2017) cannot easily be transferred to Europe, having distinctive socioeconomic profiles, urban morphologies, and transportation patterns (van de Coevering and Schwanen, 2006). Third, methodological uncertainties may also play a role concerning a lack of universal findings (Trudeau et al., 2023). For example, though theoretically not justifiable, studies typically assume that the associations are linear. Another study suggested that the results may be sensitive to how socioeconomic indicators are used and are dependent on the noise source under investigation (Peris and Arguelles, 2023), highlighting the necessity for additional research.

Due to the paucity of national noise inequality studies in Europe, in this paper, we fill these gaps in the state of research by conducting a small-area study in the Netherlands. We aimed to examine the possibly non-linear associations between environmental noise levels, demographic, and socioeconomic neighborhood compositions. Based on the current knowledge base, we hypothesized that socioeconomically disadvantaged neighborhoods and those with a high proportion of ethnic minorities are associated with greater noise. Next, neighborhoods with pronounced younger or older people and higher employment rates might suffer less from noise pollution, as do less urbanized neighborhoods. Despite social equity being a pillar of the Sustainable Development Goals, noise is still absent from any of the 169 targets (United Nations, 2016); yet remains a barrier to sustainable development (King, 2022). Along these lines, our timely analysis responds to calls to action and may guide policymakers to realize equitable planning efforts when framing future environmental justice targets so that no one is left behind (Ganzleben and Kazmierczak, 2020).

## 2. Materials and methods

### 2.1. Study area

The Netherlands provided an excellent case for our cross-sectional study. A European country-wide comparison of environmental health inequalities showed that in the Netherlands, self-reported noise annoyance follows an income gradient (World Health Organization, 2019). Those in the lowest quintile showed the highest prevalence of noise annoyance. Our study was conducted on the neighborhood level ('buurten') for 2021, the most fine-grained scale with rich demographic and socioeconomic data. Further, the neighborhood level reflects that some noise sources (e.g., road traffic noise) typically disseminate over small distances.

There were 13,885 neighborhood units. Of those neighborhoods, we excluded units with incomplete covariate information, unpopulated, not on the mainland, and privacy-protected due to insufficient residents ($N = 4{,}498$). We did a complete case analysis relying on 9,372 neighborhoods with a median size of 0.567 km$^2$ (standard deviation [SD] ±5.372) and a median population of 1,265 (SD ± 1,755).

### 2.2. Modeled long-term environmental noise

Estimates of environmental noise pollution were based on the Standard Model Instrumentation for Noise Assessments (STAMINA) for large-scale noise mapping developed by the Dutch National Institute for Public Health and the Environment (Schreurs et al., 2010). STAMINA extends the point-based standardized Dutch noise calculation to the area level nationally, implementing the European Environmental Noise Directive (i.e., END 2002/49/EC). The model incorporates roadway traffic, railway traffic, industrial noise, and wind turbines as sources to obtain average estimates of the day–evening–night noise levels ($L_{den}$) in decibels (dB(A)). In contrast to noise levels between 7:00 and 19:00 ($L_{day}$), an additional penalty of 5 dB(A) is used for evening noise between 19:00 and 23:00 ($L_{evening}$), and a 10 dB(A) penalty for nighttime noise between 23:00 and 7:00 ($L_{night}$). These penalties are assigned based on the assumption that noise during the evening and nighttime causes more of a disturbance. $L_{den}$ is calculated as follows (Schreurs et al., 2010):

$$L_{den} = 10\,log\left(\frac{12}{24} \times 10^{\frac{L_{day}}{10}} + \frac{4}{24} \times 10^{\frac{L_{evening}+5}{10}} + \frac{8}{24} \times 10^{\frac{L_{night}+10}{10}}\right) \quad (1)$$

Estimated road and rail traffic noise ($L_E$) emission levels are determined at the source location $i$. While traffic noise depends on the road surface, traffic speed, and the intensity of the vehicle type, rail traffic noise depends on the railway stock, speed, and superstructure. As shown in equation (2), the noise levels are then attenuated due to geometric spreading ($A_{Geo}$), air absorption ($A_{Air}$), ground impedance (e.g., grass vs. asphalted) ($A_{Ground}$), noise barriers (e.g., buildings) ($A_{Barrier}$), and a meteorological correction ($C_{Meteo}$) which considers varying wind directions and temperature gradients. Finally, because noise diffuses spatially, a correction factor of 58.6 dB is subtracted from $L_E$ (Schreurs et al., 2010).

$$L_{den,i} = L_{E,i} - A_{Geo,i} - A_{Air,i} - A_{Ground,i} - A_{Barrier,i} - C_{Meteo} - 58.6 \quad (2)$$

Industrial sources follow a similar calculation but represent point-based emission sources rather than line-based ones (i.e., streets, railroads). Different noise propagation levels are assigned depending on the use of the site. For instance, a shipyard has an emission estimate of 70 dB (A)/m$^2$, while a warehouse only emits an estimated 55 dB(A)/m$^2$ (Schreurs et al., 2010). Wind turbine noise emissions are estimated by fitting a logarithmic curve to the noise levels obtained from the Dutch wind turbine models used at certain wind speeds and average wind speeds, lower at night and higher during the day (Schreurs et al., 2010).

Since our study centers on overall environmental noise pollution, we used the estimated cumulative noise levels for 2021 obatined from the Environmental Health Atlas (Dutch National Institute for Public Health and the Environment). The gridded noise surface has a spatially varying resolution depending on the distance to the noise emission sources. The lowest spatial resolution is 80 × 80 m, the highest is 10 × 10 m. We averaged the grid cell values onto each neighborhood representing our outcome variable. We used the *R* software 4.2.2 (R Core Team, 2023) and the packages '*terra*' (Hijmans, 2023) and '*sf*' (Pebesma, 2018) for the data processing.

### 2.3. Independent variables

Socioeconomic and demographic area-level data were uniformly aggregated to each neighborhood. Informed by previous environmental justice studies (Nega et al., 2013; van Velzen and Helbich, 2023), we included seven routinely collected independent variables. Unless stated otherwise, these variables were acquired from Statistics Netherlands referring to the year 2021.

First, we obtained proxy measures representing area-level socioeconomic status (Hajat et al., 2015). Because socioeconomic status typically comprises multiple dimensions (Berkman et al., 2014), we included the percentage of low-income residents (i.e., residents who are in the lowest 20 % of earners compared to the Dutch average), the percentage of highly educated residents (i.e., those with a bachelor's degree or higher), and the percentage of employed people. Second, because some studies indicated that migrants tend to experience higher levels of noise pollution (Casey et al., 2017; Chakraborty and Aun, 2023; Tonne et al., 2018), we adjusted for the percentage of residents with a non-Western migration background (i.e., primarily from Morocco, Antilles, Aruba, Surinam, and Turkey). Third, as an additional demographic factor, we controlled for two physiologically vulnerable age groups put at risk due to environmental stressors, namely the proportion of children and adolescents (i.e., those aged ≤15) (Stansfeld and Clark, 2015) and elderly people (i.e., people aged 65+) (Van Kamp et al., 2013). Fourth, the degree of urbanicity is often associated with higher noise pollution (Stansfeld et al., 2000). We included the number of addresses per $km^2$ to include such geographic noise variations.

### 2.4. Statistical analysis

#### 2.4.1. Descriptive and exploratory analysis

Mean and SD were produced to summarize the data. To assess possible exposure differences, we stratified the demographic and socioeconomic variables by the noise quintiles. Additionally, we quantified the neighborhood-level noise inequalities using the spatial decomposition of the Gini coefficient available in the *R* package '*lctools*' (Rey and Smith, 2013). The Gini index ranges between 0 and 1 as a descriptive summary measure and is determined based on the Lorenz curve representing the cumulative noise distribution. While zero expresses perfect equality, higher Gini values refer to greater inequality (i.e., a smaller portion of neighborhoods face a larger share of noise exposure) (Farris, 2010). We used the global and local Moran's *I* to assess neighborhood-level noise patterns. Statistical significance was tested with 999 Monte Carlo simulations. We assessed the bivariate correlations across the variables using Spearman's correlation coefficients.

#### 2.4.2. Regression analysis

We regressed neighborhood-level noise onto the complete set of independent variables using ordinary least squares (OLS) (Model 1). The variables entered the model log-transformed, and 0.1 was added to those variables with a minimum of zero. Possible multicollinearity was inspected through variance inflation factors (VIFs). A VIF threshold value of five was set to identify multicollinearity issues (Kim, 2019). Because OLS regression assumes residual independence, we used the Moran's *I* with a *k*-nearest neighbor weight matrix specification to test for residual spatial dependency. The range is typically between −1 and +1. Positive values indicate positive spatial autocorrelation, and negative values indicate negative spatial autocorrelation (Bivand, 2022). Statistical significance was tested through 999 Monte Carlo simulations. The *k*-nearest neighbor approach was deemed suitable because of the irregularly distributed neighborhood units of differing sizes, and some areas had no data due to privacy protection or were not inhabited. Since there is no one-size-fits-all solution for the user-specified parameter *k* (Arbia, 2014), we tested values between 3 and 15, but the Moran's *I* of all specifications pointed to residual spatial dependency necessitating spatial econometrics (Anselin and Bera, 1998).

We used the (robust) Lagrange Multiplier (LM) test to determine whether the spatial lag or spatial error model was more suitable for our data (Anselin and Bera, 1998). The robust LM test suggested using a spatial lag rather than an error model. The lag model (Model 2) extends the OLS model by considering the influence of neighboring observations on the response. A spatial weights matrix determines how neighboring observations are weighted in calculating the lagged variable. As for the Moran's *I*, we tested 3 to 15 nearest neighbors, while $k = 4$ resulted in the best model fit assessed through the Akaike information criterion (AIC). Lower AIC scores are favored. Due to the spatially lagged nature of the response, the estimated parameters cannot be understood as per standard practice (Arbia, 2014). Thus, we report the average total impact, capturing the sum of direct and indirect impacts of an independent variable on the response. The '*spatialreg*' package was used for model fitting (Bivand, 2022).

Because the spatial lag model is less capable of modeling complex non-linearities in the associations (e.g., polynomials may cause multicollinearity issues), we opted to fit a generalized additive model with a Gaussian link function in our secondary analysis (Model 3) (Wood, 2017). The independent variables were incorporated non-parametrically using thin-plate regression splines. We assessed collinearity among the smoothers using measures of concurvity. To account for the spatial dependence structure in our data, we modeled spatial correlations by a Markov random field smoother based on *k*-nearest neighbor ($k = 4$). The degree of nonlinearity of each variable was measured by the effective degrees of freedom. A value close to 1 represents a linear association. We used the '*bam*' function in the '*mgcv*' R package designed for large datasets (Wood et al., 2017).

## 3. Results

### 3.1. Univariate statistics

On average, the noise level of the neighborhoods was 52.1 dB (SD ± 5.8 dB). The interquartile range was 8.9 dB (1st quartile: 48.7, 3rd quartile: 55.9). Fig. 1 shows the variation of the annual average noise levels. Noise varied by region, which appeared to be higher in the Randstad area, including Amsterdam, Rotterdam, Utrecht, and The Hague. As anticipated, rural areas in the northeast and south of the Netherlands have relatively low noise levels. Neighborhoods with the highest noise pollution were next to major roads and highways, near airports (i.e., Schiphol airport), and industrial sites (Fig. 1). Table 1 reports some summary statistics of the variables. Independent variables are mapped in Supplementary Fig. S1.

We computed the Lorenz curve and the Gini index to quantify possible distributive noise inequalities, as displayed in Supplementary Fig. S2. The Lorenz curve is close to the line of equality (dashed line), and the spatial Gini index decomposition reveals that the main source of inequality is from neighborhoods that are not adjacent (Gini = 0.062, $p < 0.01$), as opposed to neighboring neighborhoods where the Gini index is close to zero.

As shown in Fig. 2, we grouped the area-based noise levels into quintiles (i.e., the 1st quintile refers to the lowest noise levels) and assessed how the independent variables vary accordingly. Some differences were noticeable. While the employment rate and the population under 15 remained relatively constant across the noise quintiles, other socioeconomic characteristics varied greatly. For example, neighborhoods with a high proportion of non-Western migrants were disproportionally exposed to high noise levels. In contrast, neighborhoods with higher rates of low-incomers and those with more academically educated people faced more noise. Denser populated areas showed a more pronounced exposure to noise.

Noise levels were significantly autocorrelated (Moran's $I = 0.599$, $p = 0.001$), suggesting the possible need to incorporate spatial dependence in the regression. Results of the local Moran's *I* supported these impressions and indicated significant ($p < 0.05$) noise hotspots (i.e., neighborhoods with high noise levels are surrounded by ones with high noise levels) (Supplementary Fig. S3).

### 3.2. Correlation analyses

Supplementary Fig. S4 summarizes the results of the correlation coefficients. Noise levels (NOI) were significantly associated with the other independent variables ($p < 0.05$). The highest correlation of 0.57 was between noise and non-Western migrants (NWES). We observed a moderately strong correlation of 0.72 among the independent variables between non-Western migrants (NWES) and address density (DENS). A

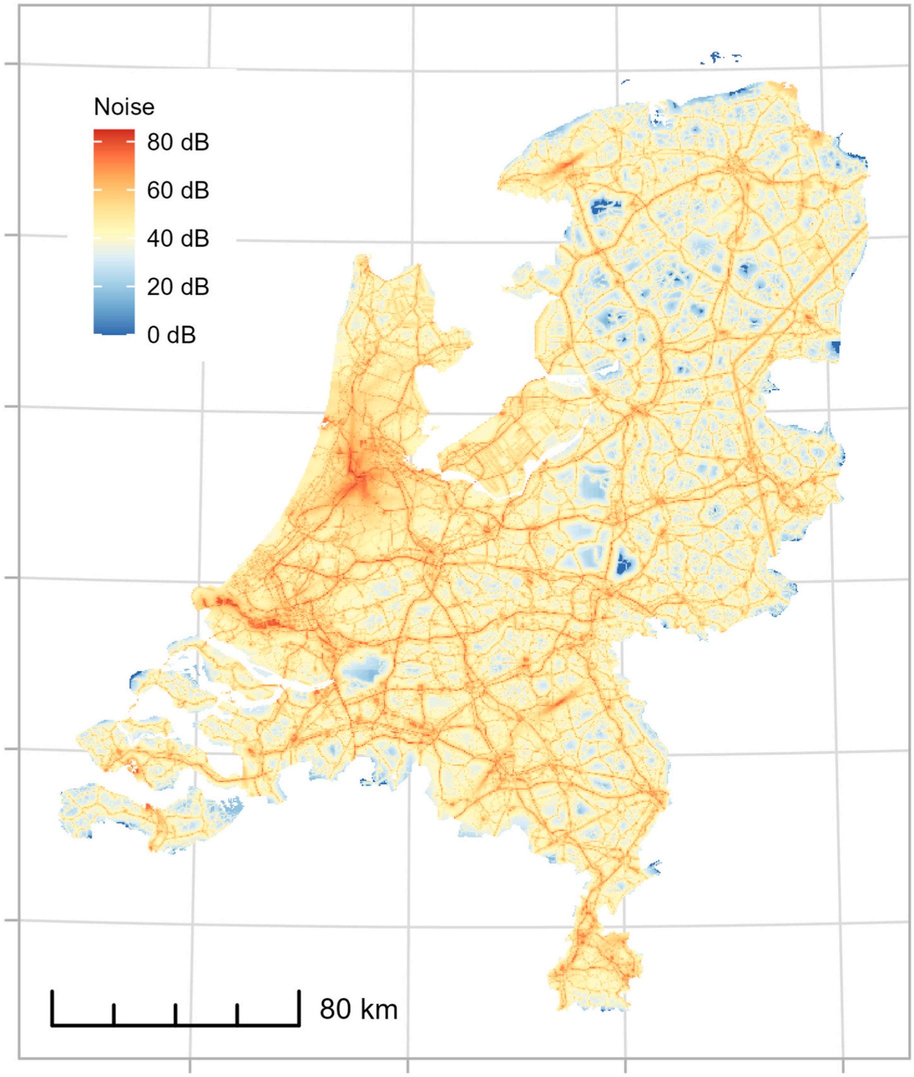


**Fig. 1.** Gridded annual average noise estimates for the Dutch mainland based on the STAMINA model (data source: Environmental Health Atlas).

**Table 1**
Descriptive statistics.

| Variable | Abbreviation | Mean | SD |
|---|---|---|---|
| Annual average noise levels | NOI | 52.14 | 5.83 |
| Population aged under 15 ( %) | YOUN | 15.15 | 4.72 |
| Population aged 65+ ( %) | OLD | 20.78 | 8.71 |
| Population of non-Western migrants ( %) | NWES | 10.14 | 11.97 |
| Employment rate ( %) | EMPL | 70.23 | 7.57 |
| Population in the lowest 20 % of earners ( %) | INC | 5.55 | 4.38 |
| Population with a bachelor's degree or higher ( %) | HEDU | 23.70 | 11.36 |
| Address density (per km$^2$) | DENS | 4283 | 4079 |

moderate negative correlation (−0.59) was seen between the proportion of low-income residents and employment rate (EMPL), while a positive one (0.58) was observed between the proportion of non-Western migrants and low-income residents (INC).

### 3.3. Regression results

We fitted an OLS regression to further quantify the descriptively found inequalities. The highest VIF value was 2.598 (NWES), falling below the cut-off value of five. The assessment of the OLS residuals indicated significant residual autocorrelation (Moran's $I = 0.383$, $p < 0.001$), rendering inference likely biased. The robust LM test suggested a spatial lag model as an alternative. As indicated by the AIC, the lag model (−22,183) performed better than the OLS model (−18,609). The lag model's Nagelkerke $R^2$ was 0.592. Since Moran's $I$ has become insignificant, the lag model appropriately incorporates residual autocorrelation (Moran's $I = -0.012$, $p = 0.952$). This is further supported by the statistically significant spatial autoregressive parameter of 0.613 ($p < 0.001$).

Fig. 3 and Supplementary Table S1 summarize the corresponding total impact effects of the lag model. Logged address density and logged employment rate were positively associated with logged neighborhood-based noise levels. In contrast, the logged population with a bachelor's degree showed an inverse association, as did low-income neighborhoods, but it did not reach statistical significance ($p = 0.080$). While non-Western migrants were positively associated with noise, the logged population aged under 15 was inversely associated. A null association was observed for the population aged 65+ ($p = 0.273$). Our regression results were robust to a different number of nearest neighbors for model fitting and refitting the model without address density, which is correlated with noise.

In our secondary analysis (Model 3), we fitted a generalized additive model, resulting in a lower AIC score (−33,006) than the linear models. No significant positive residual spatial autocorrelation was present. We observed no issues of collinearity among the smoothers. Fig. 4 and

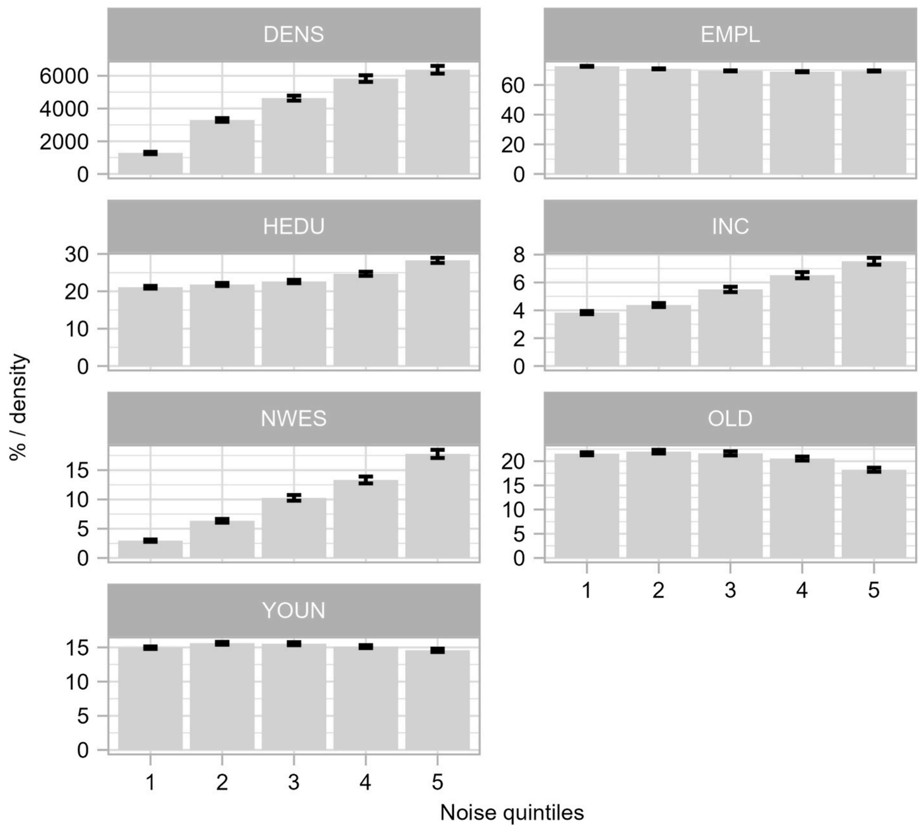


**Fig. 2.** Mean socioeconomic neighborhood characteristics per noise quintile. The 1st quintile refers to the lowest noise levels and the 5th quintile to the highest noise levels.

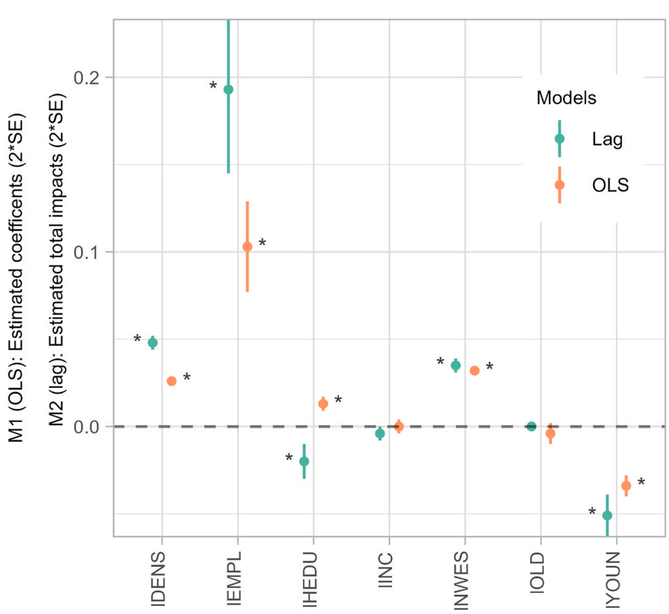


**Fig. 3.** Estimated associations based on the OLS model (Model 1) and the spatial lag model (Model 2). The estimates for the lag model refer to the total impacts. Estimates are reported with two times the standard error. Significant independent variables at the 5 % level are labeled with '*'. We log-transformed the variables before model estimation.

Supplementary Table S2 summarize the results for the smoothing splines. Each smoother was statistically significant. The effective degrees of freedom were between 3.6 and 7.7, indicating (partly substantial) non-linearities (e.g., address density). While low-income neighborhoods showed null associations in the lag model, the smoother indicated that beyond a threshold value, the association turned positive. Similarly, the association for the population aged 65+ was U-shaped. Despite some deviation from linearity, the other smoothers roughly resembled the results of the lag model.

## 4. Discussion

Environmental noise is gaining recognition as a threat to human health, with certain populations disproportionally affected. In this nationwide study, we assessed the associations between noise levels and those demographic and socio-economic population groups that suffer the most, with the goal of suggesting actions to mitigate inequality in noise exposure.

### 4.1. Main findings and interpretation

Consistent with our hypothesis, our results indicated socioeconomic disparities in noise levels across the Netherlands. Despite the European Environmental Noise Guidelines advising average road traffic noise levels below 53 dB to mitigate health effects (World Health Organization, 2018), our descriptive statistics revealed that 46 % of the neighborhoods exceeded this limit, posing potential health risks to residents.

Our results also indicated that neighborhoods with higher employment rates are positively associated with noise levels. Such a finding contradicts, for example, Lagonigro et al. (2018) for Barcelona, where areas with higher unemployment rates were overexposed. Similar ecological results were reported for Ghent, Belgium (Verbeek, 2019). However, a person-level study in Greater London concluded the opposite by reporting a null relation between neighborhood noise levels and employment rates (Xie and Kang, 2010).

Unlike Trudeau et al. (2023), who reported that education is

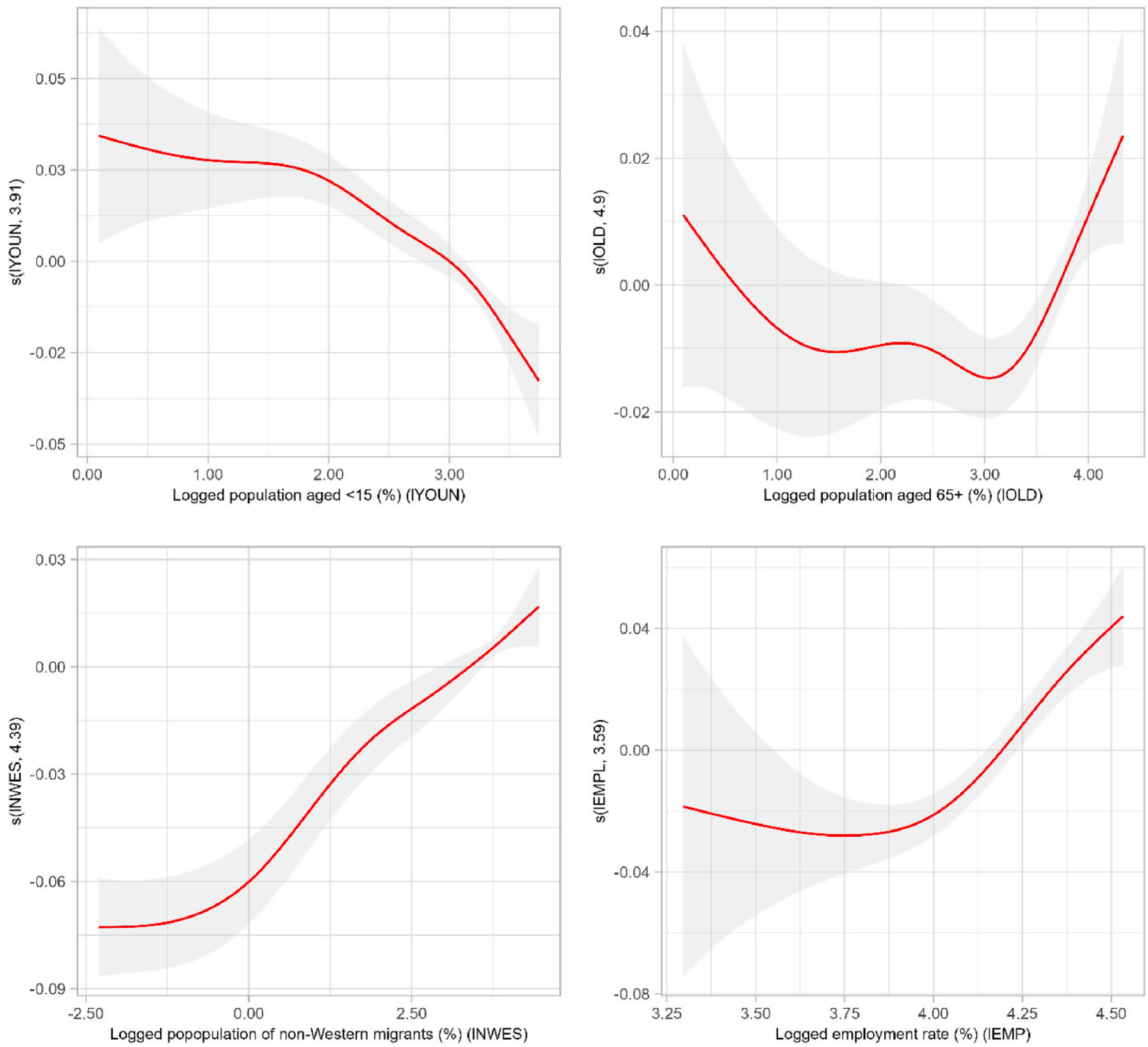


**Fig. 4.** Estimated non-linear associations (Model 3). Smoothers were obtained through a generalized additive model with a Markov random field. The associated shaded regions around the smoothers represent the 95 % confidence intervals. The corresponding effective degrees of freedom are given in brackets on the *y*-axis. We log-transformed the variables before model estimation.

infrequently related to noise exposure, our area-level indicator on education reached statistical significance. Confirming our hypothesis, we observed a negative association between noise and the proportion of academics. Our finding may be attributed to reduced social capital in less-educated neighborhoods, limiting their capacity for political intervention to address noise issues (Dreger et al., 2019). This result corroborates another ecological US-based analysis where those with at least a high school education were underexposed (Casey et al., 2017). In Europe, the findings varied (Dreger et al., 2019), possibly due to various analytical scales and ways to capture the high/low-educated (Peris and Arguelles, 2023).

Counter expectation, we found a null association between low-income neighborhoods and noise in the lag model. It turned out, however, that the association was significant in neighborhoods with a substantial proportion of low-income residents, echoing a US study (Casey et al., 2017). Other studies also reported inverse associations with income, regardless of the study design, as a review revealed (Trudeau et al., 2023). It is commonly assumed that low-income neighborhoods are more vulnerable due to limited resources and fewer coping strategies, as a population-based German study among adults reported (Kohlhuber et al., 2006).

Our findings revealed a significantly positive association between communities with more migrants and higher noise levels. Such over-exposure of noise is well-documented; for example, in a person-level study in London (Tonne et al., 2018) and an area-level US study (Casey et al., 2017). The former found that the odds of living within a 50 dB contour of rail noise were significantly higher for Afro-Americans than for white people, while in the latter, higher census block-based noise levels were associated with more non-white residents. Two explanations could support our findings. Native and Western residents may have higher geographic mobility to avoid environmental hazards, while non-Western migrants cannot do the same, leaving them in more polluted areas (Downey and Hawkins, 2008). Further, it could be that ethnic neighborhoods predominantly feature more sources emitting environmental noise (Trudeau et al., 2023).

Concerning vulnerable communities, our association of the proportion of children and adolescents with noise was, as anticipated, negative and consistent with prior studies (Lagonigro et al., 2018). It appears plausible that healthy neighborhoods act as an attractive force (Liu, 2001). Consequently, households may disproportionately gravitate towards less noisy neighborhoods, particularly when raising children. The association associations between elderly people and noise followed a

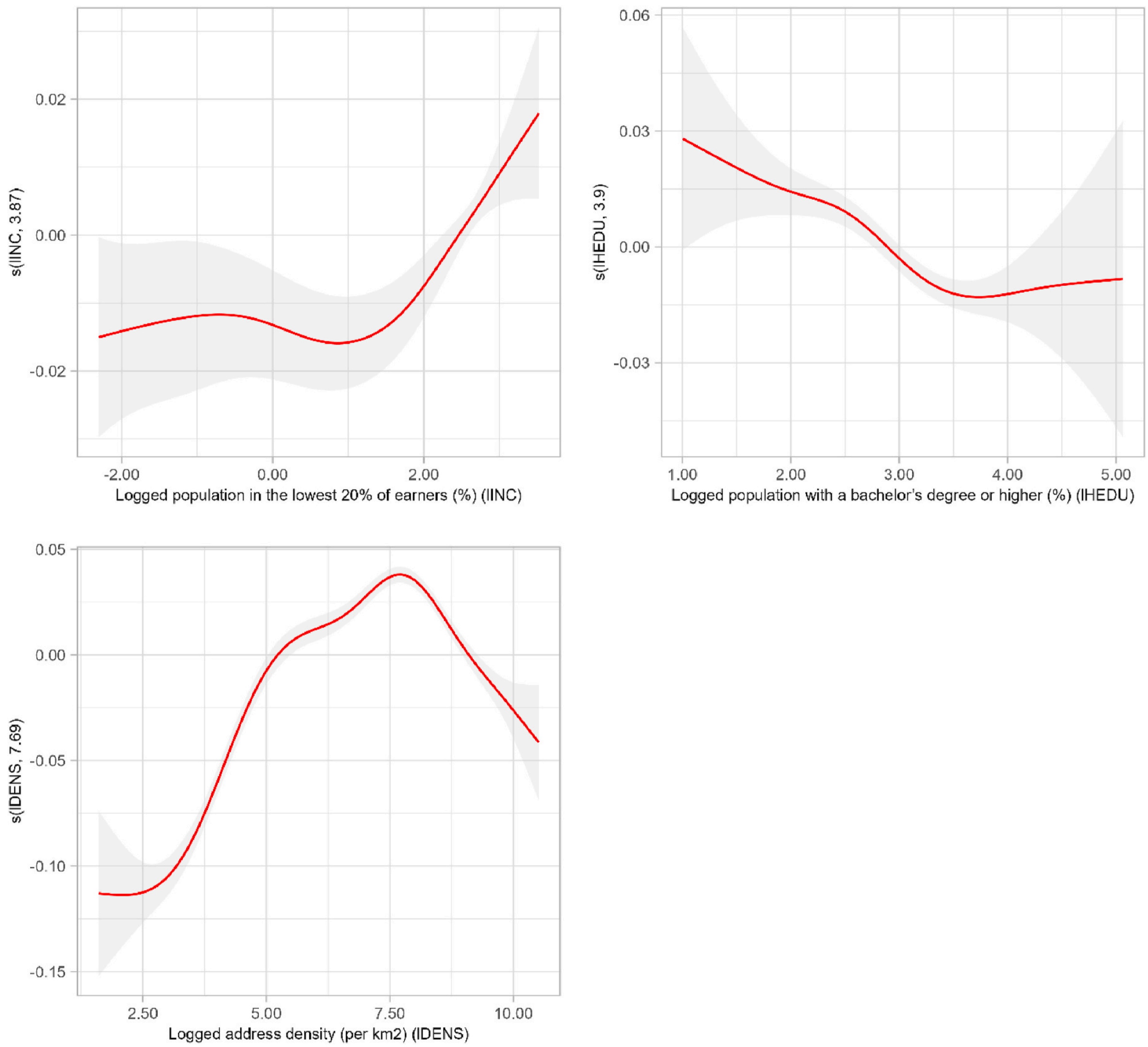


**Fig. 4.** (*continued*).

U-shape, which was not captured in the linear model. The evidence base considering elderly people is heterogeneous, and associations usually assumed to be linear remain inconclusive (Trudeau et al., 2023). For example, an area-level study in Birmingham (UK) yielded similar results to ours, showing no differences (Brainard et al., 2004). However, noise levels in Barcelona were positively associated with old age (Lagonigro et al., 2018). The latter may be due to limited mobility and restricted freedom to choose residential neighborhoods, often influenced by financial constraints and accessibility considerations.

Finally, as expected, we found that the higher the urbanization level, the higher the noise pollution; a finding is well-supported by the literature (Dreger et al., 2019; European Environment Agency, 2018). This observation is likely due to more vehicular and human activities (Stansfeld et al., 2000), while noise-absorbing features such as green spaces are scarcer. The movement of vehicles (e.g., buses) on roads generates significant noise, especially during peak hours.

### 4.2. *Strategies to achieve an equitable noise distribution*

The European Commission has recognized environmental noise as a pollutant requiring reduction. As part of its Zero Pollution Action Plan, it has proposed a policy target to decrease the proportion of individuals chronically disturbed by transport noise by 30 % by 2030 (European Commission, 2023). Achieving this goal necessitates pinpointing the population most affected by noise exposure as a priority (European Environment Agency, 2018). Research endeavors like ours are crucial for identifying such unequal distribution of noise exposure, which goes unnoticed by policymakers to continue progressing towards a more sustainable, equitable future.

Reducing engine, exhaust, and rolling noise is generally crucial in tackling urban noise pollution, regardless of population strata. This can be achieved by addressing sources directly and environmental interventions (Van Renterghem et al., 2015). The former can be achieved by imposing lower speed limits (e.g., 30 km/h) for motorized traffic in urban areas where noise-reducing infrastructure is difficult to realize (Brink et al., 2022; Nieuwenhuijsen, 2020). While such strategies are not explicitly tailored to address environmental inequalities, actionable policy lessons are also needed to protect the most exposed. For instance, enhancing green spaces, particularly in priority areas, including less affluent neighborhoods, can be a cost-effective nature-based solution. Besides health benefits (Twohig-Bennett and Jones, 2018), vegetation enhances living conditions and can buffer noise between 9 dB and 11 dB, depending on the tree's leaf surface area (Ow and Ghosh, 2017).

It seems vital to prioritize vulnerable neighborhoods for financial subsidies to improve the effectiveness of soundproofing homes and warrant affordable housing options in quieter neighborhoods. To counter widening population inequalities, we plea for inclusive urban planning (Pineo, 2022) to ensure that noise exposure is fairly distributed, regardless of the socio-economic status of a neighborhood, to create more equitable living conditions for all residents (Nieuwenhuijsen, 2020).

### 4.3. Strengths and limitations

This study possessed various strengths. Diverging from most scholarship focused on individual cities (Clark et al., 2022; Huang et al., 2021), our study was one of the few national analyses. While previous studies investigated environmental disparities, primarily concentrating on air pollution (Jbaily et al., 2022; Liu et al., 2021), our focus centered on noise pollution, a less well-explored environmental factor. Additionally, incorporating diverse neighborhoods along the urban-rural gradient enriched our findings, offering more nuanced results than exclusively focusing on individual cities. Our non-linear and spatially explicit modeling approach successfully overcame the methodological challenges of geographically correlated neighborhoods, a deficiency that likely biased the estimates in previous studies (Brainard et al., 2004). Another notable strength was the aggregation of noise levels on a small scale, allowing us to depict noise variations accurately while minimizing the risk of aggregation errors. Nonetheless, future studies are advised to model noise exposure disparities on an individual's address over the residential history (Hagedoorn and Helbich, 2021) and along their daily mobility (Kim and Kwan, 2021) rather than assessing ecological associations.

Despite these strengths, certain limitations need to be emphasized. Our noise metric did not distinguish between various noise types, leaving us uncertain about whether a particular type of noise is accountable for the observed inequalities. We used mean environmental noise levels as the response variable, but this operationalization overlooks potential within-neighborhood heterogeneity. As the observed associations were on the neighborhood level, we cannot rule out that employing different analytical granularities may yield slightly different effect estimates (Tian et al., 2024), as indicated by the Modifiable Areal Unit Problem (Openshaw, 1981). Correspondingly, inherent in the ecological study design, drawing inference about individuals is inappropriate (Freedman, 1999). Another limitation pertained to the model adjustment. While we adhere to the literature in selecting our area-level variables, it is possible that certain variables were not included in the analysis. For example, as done elsewhere (Casey et al., 2017), we did not include a population-based segregation measure. Finally, due to the cross-sectional nature of the data, the reported associations do not enable causal interpretations, as is the case for most similar studies (Clark et al., 2022). For more robust longitudinal associations and to ascertain whether the observed inequalities persisted or exacerbated over time, future research should employ panel models that can account for time lags and unobserved confounders.

## 5. Conclusions

The pervasive environmental noise emitted from anthropogenic activities has become a concern for human health. This burden is, however, not shared equitably geographically or socioeconomically. Accompanying the environmental inequality in city-specific studies, our national findings from the Netherlands support the notion that neighborhoods with more non-Western migrants, employment rates, and address density were positively associated with noise pollution. Low-income neighborhoods were only associated with noise beyond a threshold value. We observed negative neighborhood-level associations with a higher proportion of academics and neighborhoods with more younger residents. Neighborhoods with a higher share of older people showed a U-shaped association with noise. Our results further revealed that such discrimination may be exacerbated through the geographic context; more urbanized neighborhoods were especially associated with increased noise pollution. The models emphasized the significance of considering spatial effects between neighborhoods and non-linearities in the associations.

To address environmental injustice, our study underscores the necessity of implementing policy measures that extend beyond generic one-size-fits-all noise mitigation strategies. We advocate for place-based noise interventions that are socially tailored to efficiently tackle the root causes of environmental stressors; otherwise, we pose the risk of certain vulnerable and less privileged population groups being disproportionately affected by noise, leading to multiple jeopardy in terms of environmental burdens, and possibly widening the health disparities.

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## CRediT authorship contribution statement

**Max Hayward:** Conceptualization, Methodology, Formal analysis, Data Curation, Visualization, Writing - Original Draft. **Marco Helbich:** Conceptualization, Methodology, Formal analysis, Visualization, Writing - Original Draft, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data can be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.118294.

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