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Inequality in exposure to daily aircraft noise near heathrow airport: An empirical study

Xiangpu Gong [a,b], Nicole Itzkowitz [c], Glory O. Atilola [c], Kathryn Adams [a], Calvin Jephcote [a], Marta Blangiardo [c], John Gulliver [a,b,d], Anna Hansell [a,b,e,*]

[a] Centre for Environmental Health and Sustainability, University of Leicester, Leicester, United Kingdom
[b] The National Institute of Health Research (NIHR) Health Protection Research Unit (HPRU) in Environmental Exposures and Health at the University of Leicester, Leicester, United Kingdom
[c] MRC Centre for Environment and Health, Department of Epidemiology and Biostatistics, School of Public Health, Imperial College London, London, United Kingdom
[d] Population Health Research Institute, St George's, University of London, London, United Kingdom
[e] National Institute for Health Research (NIHR) Leicester Biomedical Research Centre (BRC), Leicester General Hospital, Leicester, United Kingdom

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ABSTRACT

Aircraft noise is an important source of environmental pollution and a burden on public health. We examined the association between three different area-level deprivation measures (Carstairs index 2011 only; yearly avoidable mortality rates 2014–2018 and yearly fuel poverty rates 2014–2018) and daily aircraft noise metrics (Lday, Leve, Lnight, and LAeq24) around London Heathrow Airport. Analyses were conducted for 2014–18 for ~155,000 postcodes using a Random-Effects model with an autoregressive term for the temporal variability of daily noise. We found that the relationship between aircraft noise and deprivation was complex, varying by the measure of deprivation and aircraft noise metric. We observed gradient relationships between avoidable death rates and aircraft noise exposure for all noise metrics. For Carstairs index, a measure of area-based material deprivation, the least deprived quintile exhibited the lowest night-time noise levels, but no gradients were observed for this or other noise metrics. Similarly, we did not see clear patterns of association between fuel poverty and aircraft noise. When stratifying the data by % non-White population, the conclusions for avoidable death rates and fuel poverty remained similar, but an association of Carstairs index with noise metrics was seen in the two tertiles with the highest % non-white population. Our strengths include our large dataset with high temporal and spatial resolution, as well as use of multiple deprivation measures and daily noise metrics over five years, that can capture dynamic changes in noise exposure related to changes in flight paths and weather conditions. Limitations include that we looked at 2014–18 and noise levels have been changing over time due to action plans to reduce exposure, and activity changes due to the pandemic and post-pandemic periods. Heathrow Airport is sited near wealthy and densely inhabited communities so may not be representative of all airports.

1. Introduction

Aircraft noise constitutes a significant contributor to environmental pollution and a substantial source of annoyance (Van Kempen et al., 2018). London's Heathrow Airport is one of the busiest airports globally, which also had the highest number of individuals affected by aircraft noise at a level classified as "significantly annoying" compared with any other airport in Europe in 2017 (UK Civil Aviation Authority, 2022). This is largely due to its location on the outskirts of densely populated west London, with approximately 3.6 million residents in its vicinity (Floud et al., 2011).

Numerous studies have examined the detrimental impacts of aircraft noise on human health. Some have established a positive association between aircraft noise and noise annoyance, with evidence suggesting that noise annoyance in Europe may have increased over time (Janssen et al., 2011; Babisch et al., 2009). Night-time aircraft noise can also wake people and disrupt their sleep (Smith et al., 2022; WHO Regional Office for Europe, 2018), and both noise annoyance and sleep disturbances can, directly or indirectly, contribute to the onset and progression of cardiovascular disease (Münzel et al., 2018). Research has indeed

* Corresponding author: National Institute for Health Research (NIHR) Leicester Biomedical Research Centre (BRC), Leicester General Hospital, Leicester, United Kingdom.

E-mail address: ah618@leicester.ac.uk (A. Hansell).

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documented associations between aircraft noise exposure and elevated blood pressure levels (Carter et al., 2002), as well as a higher risk of cardiovascular morbidity (WHO Regional Office for Europe, 2018; World Health Organization, 2009). Studies have also suggested that environmental pollutants are more likely spectrum of psychological outcomes (Clark, 2015), such as anxiety disorders (Lan et al., 2020; Beutel et al., 2016), and depression (Beutel et al., 2016).

Because of the undesirable nature of aircraft noise exposure, all else being equal, theories predict an inverse association between aircraft noise and deprivation. Sources of environmental pollutants are more likely to concentrate in marginalised communities that may lack the capacity to participate in land-use decision-making, resulting in a perceived low likelihood of collective action (Casey et al., 2017; Trudeau et al., 2023). The hedonic pricing model suggests that houses in areas with higher noise levels tend to have lower market values (Nelson, 2008). Since low-income households with lower disposable income are more likely to live in houses with lower house prices (Xu and Tang, 2014; Sobotta et al., 2007), this implies an association between noise exposure and deprivation.

However, only a small number of published studies have examined the association between noise pollution and deprivation. Dreger, Schüle, Hilz et al. (Dreger et al., 2019) conducted a review on social inequalities in environmental noise exposure in the WHO European Region, including studies published between 2010 and 2017 from countries such as France, Germany, and the United Kingdom (UK). The authors noted that it was difficult to establish general trends due to variations in how the social factors were measured (Trudeau et al., 2023; Dreger et al., 2019). In a 2023 review, Trudeau, King and Guastavino (Trudeau et al., 2023) analysed 34 published studies from Europe, North America, Accra, and Hong Kong, finding suggestive evidence of social inequality in noise exposure, particularly for low-income and racial/ethnic groups.

There is a notable gap in the literature regarding aircraft noise exposure inequality, which we aimed to address. Aircraft noise is particularly annoying compared with road and railway noise (Nguyen and Yano, 2023). Identifying the vulnerability of communities exposed to high levels of aircraft noise is an important step in addressing inequality in aircraft noise exposure. Furthermore, deprivation profoundly impacts both individual health (Townsend et al., 2023; Cui et al., 2020) and productive life (Boyce et al., 2016), and could therefore be an important confounder in examining the association between aircraft noise exposure and its health effects. However, the extent to which deprivation can confound this association has not yet been fully recognised.

We contributed to the literature by using multiple acoustic indicators and deprivation measures. Most studies that looked at the association between noise pollution and deprivation have used annual average noise levels. However, noise levels may change on a day-to-day basis. Flight path adjustments due to weather conditions, maintenance or air traffic control affect noise exposure. Meteorological conditions such as wind direction, speed, and air temperature also influence how sound travels (Lee et al., 2019). The use of long-term noise exposure in studies may not capture daily variations in noise, which could contribute to the ambiguous association between aircraft noise exposure and deprivation. Most studies used metrics such as DNL (day-night average sound level) or Lden (day-evening-night level), which do not differentiate between day and night noise. We used daily noise indicators that distinguish between day and night noise levels to examine which period was more strongly associated with deprivation. Moreover, while socioeconomic factors such as income and ethnicity have been examined in noise inequality studies, very few have investigated health inequality. To address this gap, we employed three measures of deprivation: the Carstairs index, the avoidable death rates, and the fuel poverty rates.

Another motivation for our study is to examine the interplay between deprivation, ethnicity, and aircraft noise exposure, which has not been well explored, as noted by Trudeau, King and Guastavino (Trudeau et al., 2023). Around half of the UK's ethnic minority population lives in Greater London (Steinbach et al., 2014) and communities surrounding Heathrow Airport have some of the highest levels of non-white ethnicity in the region. A study of labour market dynamics in the UK found that ethnic minority members, particularly Black African, Black Caribbean, Pakistani and Bangladeshi minorities experienced higher risks of unemployment and had lower levels of earnings (Li and Heath, 2020). Racism, discrimination, and cultural beliefs and behaviours, may contribute to health inequality (Smith et al., 2000). A study conducted in the US found evidence suggesting that decision-makers might try to please more influential constituents, resulting in a disproportionate burden of aircraft noise pollution borne by ethnic minority areas. As a result, in the US, minority populations, including Hispanic/Latino, Black/African American, and Asian communities, were more likely to reside in areas with higher levels of aircraft noise compared with non-Hispanic or White populations (Nguyen et al., 2023). To the best of our knowledge, there is very limited evidence on how ethnicity might mediate the association between aircraft noise pollution and deprivation in the UK context.

The objective of our study is therefore to examine the association between aircraft noise and multiple domains of deprivation. We also aimed to examine the interaction effect of ethnicity on this association.

2. Materials and methods

2.1. Study area, unit and period

The study period is from 2014 to 2018, for which we had available daily modelled aircraft noise data for Heathrow Airport.

We identified a boundary box, as shown in Fig. 1, that captures the outer bounds of the annual average aircraft noise contours of the Civil Aviation Authority (CAA) in 2011 (the year of the most recent national Census to the study period).

We used postcodes as the unit of analysis because they represent the smallest geographical area in the United Kingdom, allowing us to model noise levels with the highest possible spatial resolution. We included all postcodes within this boundary box. Each postcode within the study area has an average of 53 residents (SD = 44) and 22 occupied households (SD = 17) (based on NOMIS headcount data (Office for National Statistics, 2013a)). There were 155,448 to 156,324 postcodes between 2014 and 2018, with variations due to new creations and eliminations. Less than 0.25% of the postcodes changed geographic area covered during the study period.

The combined population of this boundary box in 2011 was approximately 6.3 million.

2.2. Noise data

Daily aircraft noise levels for 2014–2018 at postcodes within the study area were modelled by a noise consultancy Anderson Acoustics, with input from the authors on model parameters chosen, using version 3b of the Aviation Environmental Design Tool (AEDT), developed by the United States (US) Department of Transportation Federal Aviation Administration. For detailed information on the noise model and input data please refer to Itzkowitz, Gong, Atilola et al. (Itzkowitz et al., 2023). This provided a comprehensive set of average "A" frequency-weighted noise estimates at each postcode. We calculated daily aircraft noise levels using four commonly used metrics: Lday (07:00h–19:00h), Leve (19:00h–23:00h), Lnight (23:00h–07:00h) and LAeq24 (24-h average) (WHO Regional Office for Europe, 2018).

2.3. Deprivation

We focused on material deprivation as a key measure of inequality. We additionally used proxies of health inequality due to their direct association with health outcomes and quality of life. The three measures used were Carstairs index of multiple deprivation (available at Census

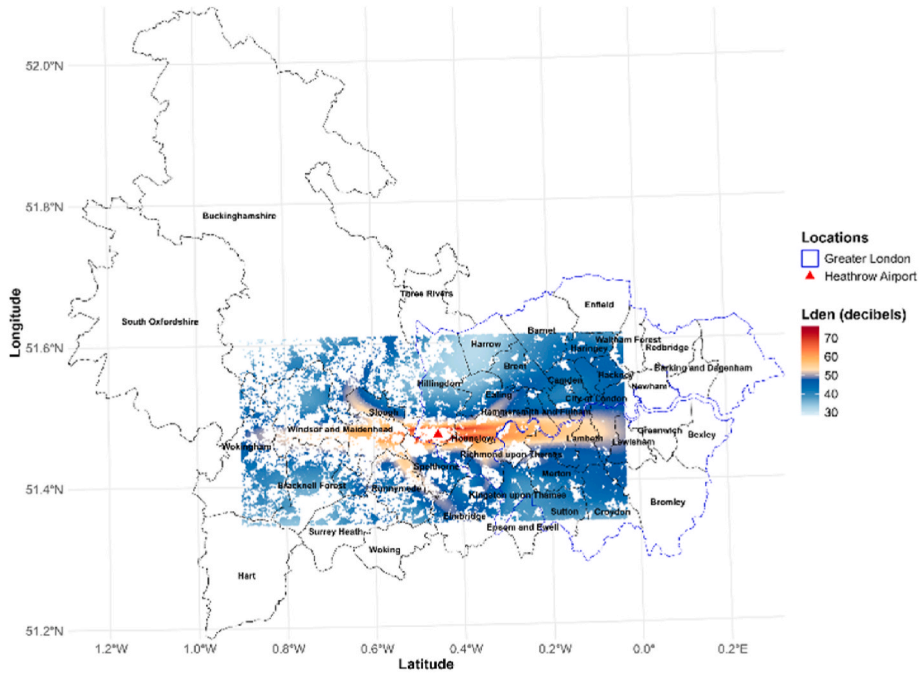

Fig. 1. Geography of the study area around Heathrow Airport, showing Local Authorities and London Boroughs boundaries and (in colour) annual average Lden noise levels for 2018 at postcodes inside the study area boundary box.

Output Areas level (COA), 2011 only), fuel poverty rates (Lower Layer Super Output Areas level (LSOA), 2014–2018), and avoidable death rates per 100,000 (Local Authority District level (LAD), 2014–2018).

2.4. Deprivation index

The Carstairs index is a commonly used area-level measure of material deprivation in health studies (Allik et al., 2016), using variables from the national Census. The nearest Census to our study was 2011, where Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Computed as the sum of standardised values from the four variables, the Carstairs index can take either negative or positive outcomes (Carstairs, 1995). Negative scores indicate lower area deprivation, while positive scores suggest higher levels of deprivation. The Carstairs index provides the highest spatial resolution among the three deprivation indicators selected for this present study, as it is based on Census Output Areas (COA), with average population size of 310 individuals. The Carstairs index is time invariant as using information from the national Census, which takes place every 10 years. The data for calculating the Carstairs index were obtained from NOMIS, and the methodology for computing this index is described in detail in Appendix Carstairs index methodology.

2.5. Avoidable deaths

Mortality is an outcome that can be clinically quantified, and avoidable mortality is amenable to policy intervention, making it a useful measure for capturing geographical disparity in health (Tang et al., 2009). We used the annual avoidable death rates per 100,000 as our second deprivation measure to capture health inequality. We used the definition of avoidable death rate from the Office for National Statistics (ONS) report Avoidable mortality in the UK: 2020, which includes deaths from causes considered avoidable, treatable, or preventable given timely and effective healthcare or public health interventions (Office for National Statistics, 2022). These data are available at the Local Authority District (LAD) level (mean population of approximately ∼179,000) and cover each year between 2014 and 2018. We downloaded the data from the Office for National Statistics (Office for National Statistics, 2023).

2.6. Fuel poverty

The final measure of deprivation is the annual percentage of households in fuel poverty, defined as those unable to maintain standard thermal comfort and safety (Liddell and Morris, 2010). The metric used to define fuel poverty in England is the Low-Income Low Energy Efficiency (LILEE). A household is classified as fuel poor if it satisfies two conditions: i) poor energy efficiency, which encompasses all households rated D or below on the Fuel Poverty Energy Efficiency Rating (FPEER) scale; and ii) households whose remaining income after spending their modelled energy expenses would be below the poverty line set by the government (Department for Business Energy and Industrial Strategy, 2022).

Fuel poverty consists of three elements: poverty, the price of fuel, and the technical quality of houses (Middlemiss, 2017; Galvin and Sunikka-Blank, 2018). Both poverty and the technical quality of houses are directly relevant to aircraft noise exposure inequality. Fuel poverty has also been increasingly recognised as a distinct form of social and health inequality (Simcock et al., 2016). Cold conditions, often a consequence of fuel poverty, are thought to contribute to excess winter deaths (Mercer, 2003). Living in a cold home due to fuel poverty has been linked to respiratory problems, arthritis, and rheumatism across all age groups, as well as mental health problems in adolescents (Dear and McMichael, 2011). This indicator is available at the Lower Layer Super Output area (LSOA) level (Census geography category with an average population of 1500 individuals) and covers the period 2014–2018. We extracted the fuel poverty data from GOV.uk (Department for Business Energy and Industrial Strategy, 2022).

2.7. Ethnicity definition

We used the 2011 Census percentage of non-White population (encompassing all Mixed, Black, Asian, Chinese and any other ethnic minority groups) per Census Output Area. The data were obtained from NOMIS via Office for National Statistics (Office for National Statistics, 2013b).

2.8. Data wrangling

Postcodes represent very small geographic areas. We utilised population-weighted postcode centroid points from the Open Geography portal (https://geoportal.statistics.gov.uk/) provided by the Office for National Statistics (ONS) to link with deprivation variables across various larger geographic units. Since postcode centroid points are single points on the map, each can be uniquely assigned to a single COA, LSOA, or LAD.

To account for potential nonlinearity in the relationship between noise and derivation (Goodman et al., 2011; Tonne et al., 2018), we categorised deprivation measures, including the Carstairs index, avoidable death rates, and fuel poverty rates, into quintiles based on the distribution of geographic units (COAs, LSOAs or LADs) that covered all studied postcodes. We converted the percentage of non-White population into tertiles, also based on the distribution of COAs that covered all studied postcodes. Geographic units include 19,624 COAs (Appendix Fig. 2(a)), 41 LADs (Appendix Fig. 2(b)), 3,834 LSOAs (Appendix Fig. 2 (c)).

2.9. Regression analyses

We examined noise levels against deprivation using daily noise data for each day between 2014 and 2018. As there may be autocorrelation when using daily data, we specified a Random-Effects model with an autoregressive term AR (1), which assumes the noise level for each day depends on that of the previous one. This allows the model to capture temporal dependencies in daily aircraft noise levels. The random effects include random intercepts or slopes for different spatial units.

The equation is specified as:

$$noise_{i,t} = \alpha + \beta_1 deprivation_{j,t} + \sum_{k=1}^{K-1} \beta_k year_{kt} + \sum_{l=1}^{L-1} \beta_l month_{lt} + u_i + e_{it} \quad (1)$$

where $e_{it=}\rho e_{i,t-1} + \eta_{it}$,

Where i represents individual postcode, t represents days, and α is the constant term. Deprivation variables are available at larger geographic units ($j = 1,\ldots J$), which correspond to COA, LAD or LSOA depending on the deprivation variable used.

The outcome $noise_{it}$, represents daily noise variables (continuous), which comprise any of four noise metrics: Lday, Leve, Lnight, and LAeq24.

We included $year_{kt}$ ($k = 2014,\ldots,2018$) and $month_{lt}$ ($l = 1,\ldots,12$) as categorical variables to account for temporal trends and seasonal variations. Year fixed effects capture the yearly changes in air traffic volume from 2014 to 2018, while the month fixed effects control for seasonal fluctuations and periodic variations, such as those due to holidays. We also included u_i, a random effect accounting for heterogeneity at the postcode level, and e_{it}, a term which accounts for spatio-temporal variability, modelled as a first order autoregression process, i.e. $e_{it=}\rho e_{i,t-1} + \eta_{it}$, where η_{it} is assumed to be independent and identically distributed (i.i.d.).

We performed separate regressions for each deprivation measure and noise metric, with four regressions per deprivation measure (Lday, Leve, Lnight, or LAeq24), resulting in a total of 12 regressions across the three deprivation measures and four noise metrics.

We post-calculated and presented average daily aircraft noise levels per deprivation quintile by adding coefficients representing the difference in noise levels between the deprivation quintile (Q2 to Q5 quintiles of Carstairs index, avoidable death rates or fuel poverty) and the corresponding reference quintile (Q1) to the constant terms α representing the mean noise levels for the reference.

To investigate the interacting impact of ethnicity on the association between aircraft noise and deprivation, we repeated the analyses for each tertile of the percentage of non-White individuals, i.e., for each deprivation and noise metric measure, we conducted three additional regressions, each focusing on one tertile of ethnicity.

We then performed regressions to examine associations between deprivation and aircraft noise metrics by year (2014–2018). This was equivalent to 5 additional regressions per measure of deprivation (Carstairs Index, avoidable death rates, or fuel poverty) per noise metric (LAeq24, Lday, Leve, or Lnight), totalling 60 additional regressions.

In our previous analyses, deprivation variables were treated as categorical. To test the linear association between deprivation variables and daily aircraft noise levels, we performed regressions using each deprivation variable as a continuous measure. This approach results in four additional regressions for each deprivation, with each focusing on one noise metric.

3. Results

3.1. Descriptive analyses

Table 1 presents a summary of the variables used in the analysis. The dataset consists of 284,165,204 day-postcode observations. 24-hour aircraft noise level per postcode was, on average, 41.6 dB. Daytime aircraft noise was, on average, the loudest (mean: 42.72 dB), followed by evening (mean: 41.50 dB) and night-time (mean: 34.75 dB). Lnight was available for 99.83% of the observations. No Lnight data were available for the first day of the study (January 01, 2014) as the computation of Lnight requires noise levels from 23:00h to 24:00h of the previous day.

The mean avoidable death rates, Carstairs index, fuel poverty rates, and % non-White population were 209.01 per 100,000 persons per LAD, 0.90 per COA, 10.18% per LSOA, and 33.70% per COA, respectively. The avoidable death rates per 10,000 people was available for 98.83% of the observations. The small sample loss is due to missing values for City of London – a business district and small borough in central Greater London, with a population of 8,600 as per the 2021 Census.

To examine how aircraft noise levels changed over the study period, we plotted smooth trends for average daily aircraft noise levels per postcode in the study area from 2014 to 2018, using the Lowess (Locally Weighted Scatterplot Smoothing) approach (Appendix Fig. 1). The figure shows that the average daily Lday and Leve levels were around 50.0 dB and 48.7 dB, respectively, in 2014, decreasing to approximately 49.4 dB and 47.9 dB, respectively, in 2018. Interestingly, daily night-time aircraft noise levels showed a more variable trend. It initially reduced from 43.0 dB in 2014 to 42.8 dB at the beginning of 2016, followed by an increase to almost 44.5 dB in early 2018, and then fell to about 42.1 dB by the end of the year.

To examine the distribution of our data, we present violin plots of all variables in Appendix Fig. 3. The violin plots show that most areas

Table 1
Descriptive summary of the variables.

Variable	N	Mean	Std. dev.	Min	Max
LAeq24	284,165,204	41.6	6.66	20.18	76.97
Lday	284,165,204	42.72	6.92	22.79	78.29
Leve	284,165,204	41.50	6.86	4.85	78.86
Lnight	283,689,925	34.75	8.60	4.64	75.34
Avoidable death rates per 10,000 persons	280,841,749	209.01	38.14	138	295.9
Carstairs index	284,165,204	0.90	3.11	−4.88	28.31
Fuel poverty %	284,165,204	10.18	3.65	1.8	29.6
% Non-white	284,165,204	33.70	20.44	0	98.4

Note: The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

experienced sound levels between 40 and 50 dB daily during daytime and evening. Lnight had a lower mean, and a slightly narrower distribution compared with Lday or LAeq24, suggesting slightly less variation in daily night-time noise levels across postcodes. Carstairs index and the percentage of non-White population display much more variation than the noise metrics.

We present a descriptive summary stratified by tertiles of % non-White population per COA in Appendix Table 1. The mean percentages of non-White population per COA for each tertile were 13.58%, 32.45%, and 60.21%, respectively.

The first tertile (the group with the lowest percentage of non-White population) was the wealthiest. It had a mean avoidable death rate of 194.7 per 100,000 per LAD, a Carstairs index of −1.52 per COA, and a fuel poverty rate of 8.6% per LSOA. In the middle tertile, the mean avoidable death rate, the Carstairs index and fuel poverty rate were 213.2 per 100,000 per LAD, 0.96 per COA and 10.3% per LSOA, respectively. The third tertile had the highest mean avoidable death rate (221.9 per 100,000 per LAD), the highest Carstairs index (3.85 per COA), and the highest fuel poverty rate (10.5% per LSOA).

There were notable differences in the areas affected by daily night- and daytime aircraft noise. The highest quintile of night-time daily aircraft noise impacted London neighbourhoods along the easterly flight path, which typically did not experience the highest daytime aircraft noise quintile (annual average Lday and Lnight noise levels for each postcode in 2014 in Appendix Fig. 4(a) and (b), respectively). In contrast, the highest (fifth) quintile of daytime aircraft noise predominantly affected postcodes outside western Greater London along the westerly flight path, as the predominant wind direction at Heathrow is westerly and flights generally take off into the wind. We present maps of Carstairs index, avoidable death rates, fuel poverty rates, and percentage of non-White population in Appendix Fig. 4(c)–4(f), respectively.

Table 2 shows the pairwise correlation coefficients between the variables in the analysis (all are continuous). The correlation coefficients between noise metrics LAeq24, Lday, Leve, and Lnight were moderate to high, ranging from 0.58 to 0.98. The correlation coefficients between different deprivation measures were relatively weak (coefficients: 0.07 to 0.41). Similarly, their correlations with the modelled noise levels were also weak, with coefficients ranging from −0.09 to 0.20. Interestingly, % non-White population exhibited a relatively strong positive correlation with the Carstairs index (coefficient: 0.74), but a weak correlation with the avoidable death rates (coefficient: 0.31).

3.2. Associations between deprivation and aircraft noise metrics

For Carstairs index, we did not observe a consistent pattern of associations with any aircraft noise metrics, as shown in Fig. 2(a). Compared with the first (least deprived) quintile (Q1), areas in the second Carstairs quintile (Q2) had significantly higher noise levels for LAeq24, Lday, and Lnight, while those in the fourth quintile (Q4) had significantly lower levels for LAeq24, Lday, and Leve. For Lnight, higher Carstairs quintiles (Q2-Q5) had an average of 1.73–2.06 dB higher noise levels than Q1, the least deprived quintile.

For avoidable death rate, we found higher avoidable death rates were generally associated with higher daily aircraft noise levels in all noise metrics (Fig. 2(b)). These increases were most pronounced in the fifth quintile (with the highest avoidable death rates), where LAeq24 increased by 0.64 dB, Lday by 0.35 dB, Leve by 1.78 dB, and Lnight by 1.17 dB relative to Q1 (with the lowest avoidable death rates). This trend was most evident for night-time noise, where the estimated daily average noise levels for Lnight increased from 34.24 dB in Q1 (lowest) to 35.40 dB in Q5 (highest).

For fuel poverty, we did not observe a clear association between fuel poverty and aircraft noise levels, as shown in Fig. 2(c). Some quintiles showed higher noise levels while others, particularly the highest quintile (Q5), showed lower noise levels for certain metrics.

3.3. Associations between deprivation and aircraft noise metrics by ethnicity tertiles

When examining avoidable death rates and fuel poverty rates stratified by area ethnicity (Figs. 3–6, and Appendix Tables 5–7), the patterns were largely similar to those observed in the non-stratified analyses (Fig. 2), i.e., a gradient was seen between avoidable death rates and all noise metrics, but there were no clear gradients for fuel poverty.

Interestingly, in areas with a higher percentage of the non-White population (tertiles 2 and 3), we saw a positive relationship between Carstairs index and noise for all four noise metrics. The first tertile (lowest % non-White population), however, showed a complex association. Postcodes with the lowest Carstairs index (Q1 and Q2) within this tertile had the highest LAeq24, Lday and Leve noise levels. In contrast, Q1 had the lowest daily aircraft noise at night (33.52 dB).

3.4. Associations between deprivation and aircraft noise metrics by year

Given changes in aircraft noise over the five years to the study, we also examined associations between deprivation and aircraft noise metrics, stratified by year (Appendix Figs. 5–7; Appendix Tables 8–11).

The yearly results for the Carstairs Index generally align with the main findings, suggesting no consistent pattern of associations between the Carstairs Index and any aircraft noise metrics overall. However, there is a year-by-year shift from negative to positive associations for Q5 (most deprived) of the Carstairs Index, particularly for Lnight (Appendix Fig. 5).

For avoidable death rates, the stratified results are generally consistent with the main findings – higher avoidable death rates associated with higher aircraft noise levels. However, there was some variability in patterns across year, especially for 2015 (Appendix Fig. 6). The stratified results also suggest an increasing trend (steeper slope) of positive associations from 2016 to 2018, especially for night-time noise indicating increasing inequality.

In contrast, for fuel poverty rates, the results by year for daytime and evening metrics suggest a tendency towards an inverse association by the end of the time period, with more deprived areas becoming associated with lower noise levels (Appendix Fig. 7). There were no clear

Table 2
Pairwise correlations between noise metrics, deprivation measures (continuous), and % non-White (continuous).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) LAeq24	1							
(2) Lday	0.98	1						
(3) Leve	0.85	0.78	1					
(4) Lnight	0.78	0.74	0.58	1				
(5) Avoidable death rates	0.16	0.14	0.14	0.20	1			
(6) Carstairs index	−0.02	−0.02	−0.04	0.06	0.41	1		
(7) Fuel poverty rates	−0.08	−0.07	−0.09	−0.01	0.07	0.36	1	
(8) % non-White	−0.08	−0.07	−0.08	0.00	0.31	0.74	0.41	1

Note: The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

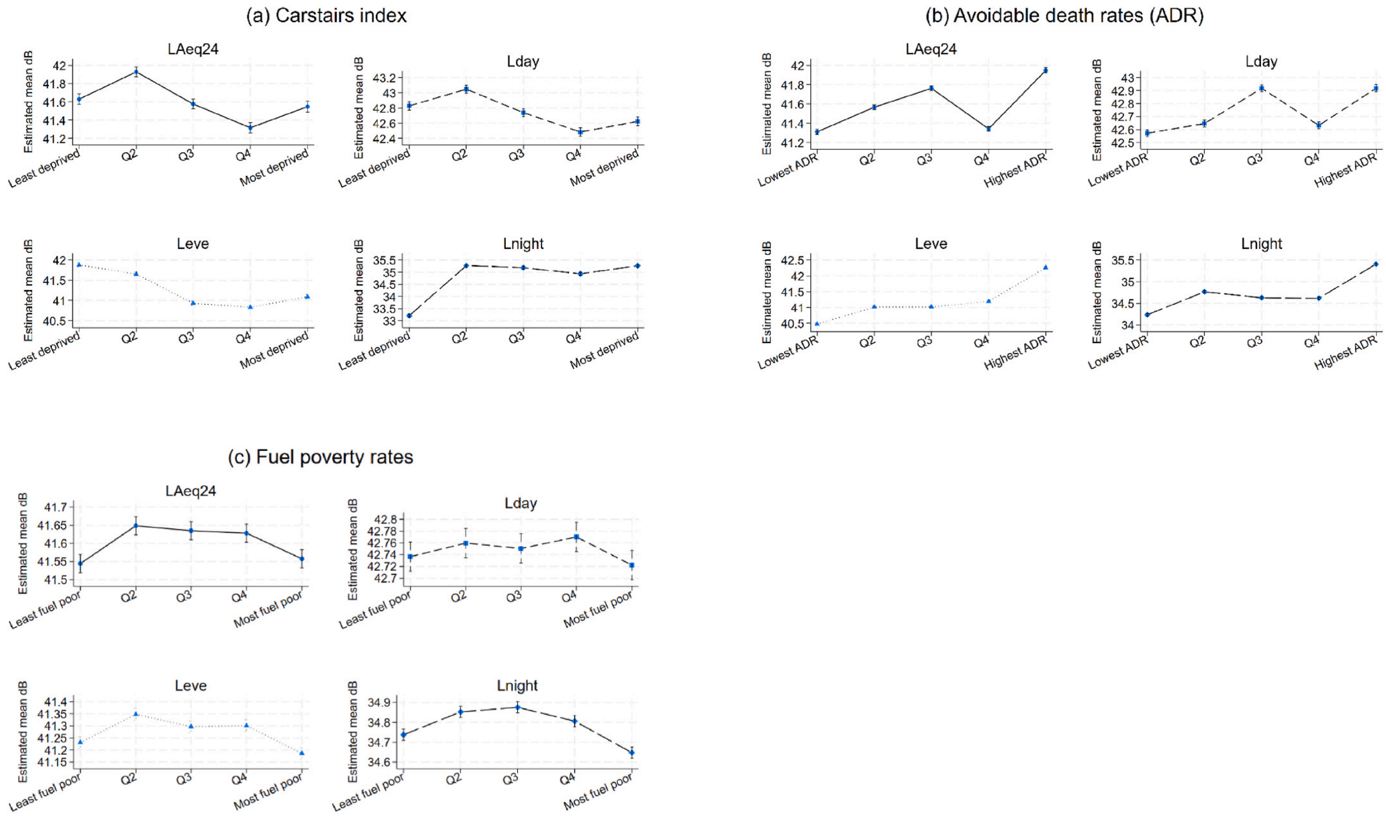

Fig. 2. Regression modelled average daily noise levels for different noise metrics by deprivation quintiles (note different scales on y-axes).
Note: Data points for the graph are from Appendix Tables 2, 3, and 4, respectively. The figures present the estimated mean daily noise levels (in decibels) across quintiles of three deprivation-related variables: the Carstairs index (material deprivation), avoidable death rates (ADR; a proxy for health inequality), and fuel poverty rates (a measure of both health and social deprivation). Noise metrics include LAeq24, Lday, Leve, and Lnight, each represented by distinct line styles and markers. The x-axis of each graph reflects quintiles from least to most deprived in (a), lowest to highest ADR in (b), or least to most fuel poor in (c), while the y-axis represents the estimated mean daily noise levels in dB. The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

trends in associations over time for Lnight.

3.5. Linear associations between deprivation and aircraft noise metrics

We also conducted an analysis using Equation (1) (in Methods) but using each deprivation variable as a continuous variable (Appendix Table 12). We found that a one-unit increase in the Carstairs index was significantly associated with a 0.16 dB increase in daily Lnight, meaning more deprived areas had higher night-time noise levels. However, the Carstairs index had negative associations with Lday, Leve, and LAeq24, meaning less deprived areas had higher day-time and 24 h average noise levels.

The avoidable death rates (Appendix Table 13) showed positive associations with Lday and Leve (areas with higher avoidable death rates were associated with higher daytime and evening noise), but negative relationships with Lnight and LAeq24, although these associations were small in magnitude.

Lastly, we observed statistically significant associations between the fuel poverty rates and daily aircraft noise levels (Appendix Table 14). There were positive associations between higher fuel poverty and Lday, LAeq24, and an unexpected negative association with Leve and Lnight, but the coefficients were all very small (Fig. 3).

4. Discussion

We investigated the association between different measures of deprivation and daily aircraft noise levels near London Heathrow Airport. Our analyses used a dataset of modelled day and night-time aircraft noise levels obtained from 155,448 to 156,324 postcodes between 2014 and 2018, which may be considered among the most detailed datasets on daily aircraft noise exposure worldwide. We found that the relationship between aircraft noise and deprivation was complex, varying by measure of deprivation and aircraft noise metric.

When examining these daily data, the violin plots clearly showed the spread of daily noise levels across different metrics (LAeq24, Lday, Leve, and Lnight). The smooth trends also demonstrated how noise levels changed over time, with some noticeable day-to-day variations that could otherwise be missed when using only long-term averages. As a result, daily noise levels may better capture daily fluctuations caused by changes in flight paths and meteorological conditions, addressing some limitations of previous studies relying on yearly averages.

The Carstairs index, a widely used area-level measure of material deprivation in health studies (Allik et al., 2016), did not show a clear gradient of associations with Lday (07:00h–19:00h), Leve (19:00h–23:00h), and LAeq24 (24-h average). However, night-time (23:00–07:00) aircraft noise levels were higher, on average, in more deprived areas, with postcodes within the most deprived quintiles of the Carstairs index experiencing 1.73–2.06 dB higher daily noise levels than those in the least deprived quintile. This provides some evidence of inequality in night-time aircraft noise exposure.

The unclear association between 24-h, daytime, and evening aircraft noise and material deprivation could be attributed to a variety of factors. Some populations appear less sensitive to airport noise (Aliyu et al., 2016). Also, proximity to the airport can provide some economic benefits, such as better access to airport-related jobs and air transportation, which can positively affect the economic well-being of residents (Cohen

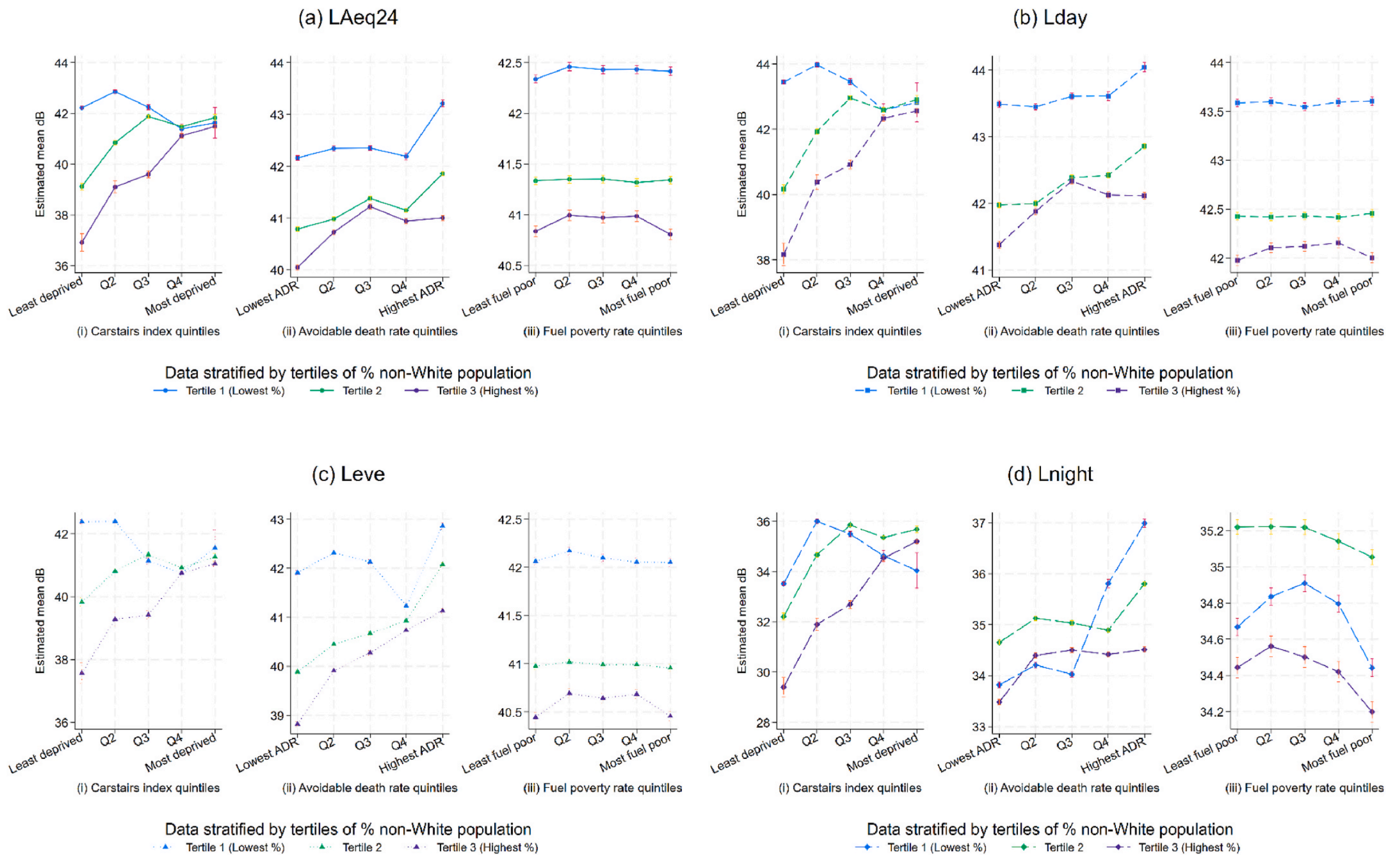

Fig. 3. Regression-modelled average daily noise levels by deprivation quintiles, stratified by tertiles of % non-White ethnicity (note different scales on y-axes). Note: Data points for the graph are in Appendix Tables 5–7 The figures present estimated mean daily noise levels (in decibels) across quintiles of three deprivation-related variables: the Carstairs index (material deprivation), avoidable death rates (ADR; a proxy for health inequality), and fuel poverty rates (a measure of both health and social deprivation). The x-axis of each graph reflects quintiles from least to most deprived in (i), lowest to highest ADR in (ii), or least to most fuel poor in (iii). The graphs are stratified by tertiles of the percentage of the non-White population (Tertile 1: lowest percentage, Tertile 3: highest percentage). Noise metrics include LAeq24, Lday, Leve, and Lnight, each represented by distinct line styles and markers. The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

and Coughlin, 2008). A study conducted in Manchester found that, under certain circumstances, residents valued positive attributes such as improved access and employment opportunities more than the negative externalities of airport proximity, such as noise pollution (Tomkins et al., 1998).

We observed that the least deprived Carstairs quintile experienced lower night-time noise levels, but not lower daytime noise. Two reasons may account for this difference. The first is that flight path patterns during the day and night were different. Moreover, it is reasonable to assume that aircraft noise may be perceived differently at night compared with during the day (van der Lippe et al., 2024), as night-time is an important period for people to recuperates. Loud night-time aircraft noise (i.e. above Leq of 50 dB) has been found to be more likely to annoy people than daytime noise (Hoeger et al., 2002). Also, residents are more likely to be at home during the night, while during the day and evening, they may be away at work—especially those in low-skilled jobs from lower socioeconomic backgrounds. Previous studies have shown that aircraft noise can disrupt sleep and has been associated with a higher risk of cardiovascular disease than daytime noise (Smith et al., 2022; WHO Regional Office for Europe, 2018; Clark, 2015). Night-time aircraft noise may therefore be seen as a greater disamenity from daytime noise, which translates to a more noticeable association between material deprivation and night-time aircraft noise levels. However, to date, most studies examining the effects of aircraft noise on house prices have used metrics such as DNL or Lden, which do not differentiate between day and night exposures (Nelson, 2004; Kopsch, 2016). Therefore, more research is needed to understand this.

The Carstairs index is more comparable to measures used in existing studies that have investigated the relationship between noise (usually road noise) and poverty. To date, evidence for the association remains limited, and ambiguous (Agency, 2018), with relatively small numbers of studies that have used different definitions of deprivation and different noise metrics. A 2022 study examining 90 airports in the US found that census block groups with a higher proportion of low-educated residents were less likely to be exposed to noise levels greater than DNL 65 dB than census block groups with a high proportion of high-educated residents (Simon et al., 2022). However, there was no evidence that lowest income census block groups were more likely to be noisy. The only other study to look at noise inequalities in exposure near Heathrow Airport, which used data obtained from the London Travel Demand Survey, concluded that individuals with the *highest* household income had a greater likelihood of living within an annual average 50 dB contour in 2010 (Tonne et al., 2018). This is not inconsistent with our findings, which looked at noise at different times of day and looked at numerical levels rather than a binary measure of above/below 50 dB.

Our analysis also found some evidence of associations between avoidable death rates and aircraft noise. Higher quintiles of avoidable death rates experienced 0.03–0.64 dB for LAeq24, 0.06–0.35 dB for Lday, 0.54–1.78 dB for Leve, and 0.39–1.17 dB for Lnight. There were more noticeable differences during the evening and night-time. Avoidable death rates, which measure mortality that is attributable to conditions that can be treated by medical intervention (Mackenbach et al., 1990), can be used to assess disparities in the quality and quantity of both health and health care in different geographical areas (Korda et al., 2007). While there are well-documented detrimental effects of noise exposure on various health outcomes (WHO Regional Office for Europe, 2018; World Health Organization, 2009), our study design is not able to assess if aircraft noise might contribute to avoidable deaths and it is not possible to conclude a causal association. Instead, our results may point to the coexistence of aircraft noise exposure and broader factors related to health and health infrastructure, for example, aspects of area-level deprivation not captured by the Carstairs index.

We found inconclusive associations between fuel poverty and daily aircraft noise (LAeq24, Lday, Leve, and Lnight). A unique feature of fuel poverty is that it can be exacerbated by outdated and inefficient home insulation (Mahoney et al., 2020; Best and Sinha, 2021), which also serves as a strategy to mitigate the negative impact of aircraft noise pollution on people. Our mixed results may be related to a lack of relationship between aircraft noise and fuel poverty or/and the coincidental decrease in the national fuel poverty in England from 17.3% in 2014 to 15% in 2018. More studies are needed to explore relationship between home energy insulation, noise insulation and external and in-home noise exposures.

When examining associations stratified by year, we found results broadly consistent with our main findings, though with some evidence suggesting higher noise levels in more deprived areas over time for Carstairs index and avoidable death rates (highest rates), relative to Q1, especially in 2017 and 2018, but a trend in the opposite direction for daytime noise and fuel poverty.

We estimated the differences in daily noise levels between higher and lower quintiles using a sophisticated statistical method. The positive estimates range from 0.01 dB to 2.06 dB, with the majority below 0.5 dB; however, we identified a few larger estimates, such as 1.78 dB and 2.06 dB. While 3 dB is often quoted as the smallest change in sound levels that is audible, this relates to acute (short-term) exposures. In this study we present sound levels averaged across a number of hours, that may be composed of a smaller number of very noisy flight events or larger numbers of events at lower noise levels; both of these scenarios would involve events likely to exceed auditory perception limits that would result in physiological and/or psychological responses. Importantly, most of the larger values were found at night, which could have health implication since this is the sleep period for most people. We examined a large number of postcodes, with each quintile containing around 30,000 postcodes.

We explored use of aircraft noise as categorical variables and as continuous variables, presenting somewhat inconsistent results. However, using linear regression assuming a consistent slope may be potentially problematic given our evidence that the relationship between aircraft noise and deprivation was shown to be complex and potentially non-linear. For example, using avoidable death rate as a categorical variable showed a positive relationship between the avoidable death rate and all noise metric categories, but as a continuous variable, it showed negative associations with Lnight and LAeq24.

Our results offer insights into the complex interplay between deprivation, daily aircraft noise and ethnic composition of communities in areas surrounding Heathrow Airport. Greater London has a diverse population, with 46.20% non-White residents in 2022 (GOV.UK, 2022). In areas with higher percentages (T2 and T3) of non-white populations, a higher daily noise pollution was associated with higher socioeconomic disadvantages, as measured by the Carstairs index or avoidable death rates. These results agree with recent research conducted by Nguyen, Levy, Kim et al. (Nguyen et al., 2023), which highlighted the disproportionate exposure of minority populations, including Hispanic/Latino, Black/African American, and Asian communities, to higher levels of aircraft noise pollution compared with non-minority groups around 90 US airports. An intriguing finding from our study is the inverse association between aircraft noise and the Carstairs index (lower noise in wealthier areas) in first tertile with highest percentage of White residents.

Our results suggest a possibility of higher daily aircraft noise exposure in some areas with higher percentages of non-White population, which also coexisted with higher health deprivation or material deprivation near Heathrow Airport from 2014 to 2018. However, the associations were less conclusive compared to studies in other countries (Bakkensen et al., 2024). Cumulative disadvantage have important policy implications, as the interactions between pollutants and non-pollutant stressors may cause nonlinear damages to well-being in local populations (Bakkensen et al., 2024). Currently, Heathrow Airport implements Night Quota periods (23:00h - 06:00h) to restrict the number of flights allowed during this period in order to protect the well-being of affected residents. We suggest that cumulative impacts from social and environmental burdens should be considered in the design and implementation of policy to address social concerns (Laurent, 2011).

Our study has several strengths and limitations. One strength is its very large and detailed dataset, with daily averaged standard noise metrics for 155,448 to 156,324 postcodes near London's Heathrow Airport. We differentiated between daytime and night-time aircraft noise, and considered different deprivation domains, including not only material poverty, but also health inequalities.

We extended the use of the AEDT model, typically used for long-term average noise exposures, to assess short time periods within a single day. Several limitations were identified, including the use of fixed meteorological constants (e.g., atmospheric pressure, humidity, and wind speed), a fixed headwind speed, and uniform sound dispersion, all of which may affect the accuracy of noise exposure estimates. The terrain model only accounts for natural landscapes, and high computational demands limit spatial resolution. To improve accuracy, we used radar tracks from Heathrow Airport, generating 14,608 flight-activity-informed noise surfaces over five years (2014–2018), with actual flight paths and unique temperature profiles for each modelled period. Several studies have validated AEDT noise estimates, such as Meister, Schalcher, Wunderli et al. (Meister et al., 2021) and Gabrielian, Puranik, Bendarkar et al. (Gabrielian et al., 2021), who reported discrepancies between modelled and actual noise levels within 2.5 dB.

Among other limitations are that the study area was designed to capture the outer bounds of the Civil Aviation Authority (CAA) annual-average 50 dB Lden aircraft noise contours in 2011. Some postcodes outside of the study area may still be affected by aircraft noise but were not included in the analysis. However, given the resolution and size of the data, it is a reasonable compromise, which may affect daytime noise results but not night-time noise results, as the study area was significantly larger than the 2011 CAA annual average night-time aircraft noise contours. We looked at 2014–18 and noise levels have been changing over time, given airport noise action plans to reduce exposure, as well as activity changes due to the pandemic and post-pandemic periods, which may change relationships with deprivation metrics. We used outdoor aircraft noise levels as a proxy for individual-level exposures (for which data are not available). Census-derived variables including Carstairs index and % non-White population, were only available for 2011 (the year of the Census). Our deprivation measures relate to differing geographic levels, some of which, such as LADs, were quite large. Avoidable death rates were only available at the LAD level. The relatively large geographic unit of avoidable death rates, which, when used with postcode-level data, may mask significant local variations in noise exposure due to the mismatch in geographic scales. For instance, the fifth quintile of the avoidable death rates experienced 2.06 dB higher average night-time noise compared with the first quintile, which is relatively small. Neighbouring postcodes may share a common noise contour level, implying spatial autocorrelation. However, due to computational constraints arising from our extensive sample size (over 155,000 postcodes) and extended time periods (over 1,800 days), we were unable to specify a spatial autocorrelation model. Finally, we note that London has a diverse multi-cultural population, with one of the world's busiest airports in relatively close proximity to populated areas, some of which are very wealthy. Findings may not be generalisable to other airports.

5. Conclusion

This study found mixed evidence for associations of daily aircraft noise with area-level deprivation measures in ~155,000 postcodes surrounding London Heathrow Airport. There were positive associations between avoidable death rates and all noise metrics used (Lday, Lnight, Leve, and LAeq24), but the associations between noise and the Carstairs index or fuel poverty were less clear. Our study is one of very few to investigate the relationship between aircraft noise and inequality. Areas with higher ethnic diversity experienced higher aircraft noise levels. A better understanding of the spatio-temporal variability in noise exposure in vulnerable groups is needed to inform effective measures to mitigate the negative effects of aviation noise pollution.

CRediT authorship contribution statement

Xiangpu Gong: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nicole Itzkowitz:** Writing – review & editing, Data curation. **Glory O. Atilola:** Writing – review & editing, Methodology. **Kathryn Adams:** Writing – review & editing, Resources. **Calvin Jephcote:** Writing – review & editing, Resources. **Marta Blangiardo:** Writing – review & editing, Methodology, Funding acquisition. **John Gulliver:** Writing – review & editing, Resources, Funding acquisition. **Anna Hansell:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization.

Data sharing statement

The aircraft noise exposure data are available to other academic researchers on request to the corresponding author.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly for Microsoft Office and QuillBot for Microsoft Word to proofread the manuscript and improve readability. After using this tool/service, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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.

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The views expressed are those of the author(s) and not necessarily those of the NIHR, Department of Health and Social Care, UKHSA, HSE or University of Leicester.

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This research used the ALICE High Performance Computing Facility at the University of Leicester.

Appendix. Carstairs index methodology

A revised form of the Carstairs index was constructed for Census Output Area (COA) and Lower Layer Super Output Areas (LSOA) in England and Wales, using the 2001 classification of low social classes devised by Norman (2002). The revised low social class variable approximates its counterpart from the 1991 Census, developed to account for ONS methodology and classification changes in later censuses.

Datasets from the 2011 census were obtained from NOMIS (www.nomisweb.co.uk), the official online delivery service of labour market statistics provided by the Office for National Statistics (ONS). Tables KS602EW, QS409EW, KS404EW, and QS607EW contained the necessary information to create the Carstairs Index for 2011, across England and Wales.

Variable 1: Proportion of “Male Unemployment” (KS602EW)	
Description	“Unemployed Males Age 16-74y” ÷ “Economically Active Males Age 16-74y”
Calculation	KS602EW0005 ÷ (KS602EW0002 + KS602EW0003 +KS602EW0004 + KS602EW0005 + KS602EW0006)

Variable 2: Proportion of “Overcrowded Households” (QS409EW)	
Description	(“Over 1 and up to 1.5 persons per room” + “Over 1.5 persons per room”) ÷ “All Households”
Calculation	(QS409EW0004 + QS409EW0005) ÷ QS409EW0001

Variable 3: Proportion of “Households without Vehicle Ownership” (KS404EW)	
Description	“No Cars or vans in household” ÷ “All households”
Calculation	KS404EW0002 ÷ KS404EW0001

Variable 4: Proportion of "Persons from a Low Social Class" (QS607EW)	
Description	(L11.2 + L12.2 + L12.4 +L12.5 + L12.7 + L13.1 + L13.2 + L13.4 + L13.5) ÷ "All persons"
Calculation	(QS607EW0035 + QS607EW0038 + QS607EW0040 + QS607EW0041 + QS607EW0043 + QS607EW0045 + QS607EW0046 + QS607EW0048 + QS607EW0049) ÷ QS607EW0001

Each of these variables were z-scored (mean-centred and divided by their standard deviation), and all four z-scores were summed to return an index value measuring the relative level of deprivation in each community. A value of 0 identifies communities that follow the national average of England and Wales, with negative values identifying increased affluence, and positive values identifying increased levels of deprivation.

Appendix. Tables

Appendix Table 1
Descriptive summary of the variables stratified by ethnic tertiles

Stratified by	Variable	N	Mean	Std. dev.	Min	Max
% non-whites	LAeq24	104,174,488	42.41	6.48	20.18	72.06
T1 (lowest concentration of non-whites)	Lday	104,174,488	43.57	6.71	22.79	73.56
	Leve	104,174,488	42.35	6.75	4.85	74.91
	Lnight	104,000,584	34.72	8.89	4.64	70.89
	Avoidable death rates per 10,000 persons	102,778,726	194.67	35.62	138.00	295.90
	Carstairs index	104,174,488	−1.52	1.78	−4.88	9.20
	Fuel poverty %	104,174,488	8.58	3.07	1.80	29.60
	% Non-whites	104,174,488	13.58	5.57	0.00	22.30
% Non-whites	LAeq24	96,326,469	41.33	6.17	22.68	75.43
T2	Lday	96,326,469	42.4	6.48	24.26	76.92
	Leve	96,326,469	41.22	6.34	10.68	77.15
	Lnight	96,165,738	35.15	8.08	5.6	72.67
	Avoidable death rates per 10,000 persons	94,404,248	213.18	37.08	138.4	295.9
	Carstairs index	96,326,469	0.96	2.17	−4.6	12.41
	Fuel poverty %	96,326,469	10.34	3.59	2.3	29.6
	% Non-whites	96,326,469	32.45	6.18	22.3	44.3
% Non-whites	LAeq24	83,664,247	40.9	7.29	21.92	76.97
T3 (highest concentration of non-whites)	Lday	83,664,247	42.04	7.53	23.91	78.29
	Leve	83,664,247	40.77	7.43	10.25	78.86
	Lnight	83,523,603	34.34	8.8	5.34	75.34
	Avoidable death rates per 10,000 persons	83,658,775	221.93	36.53	149.4	295.9
	Carstairs index	83,664,247	3.85	2.75	−4.36	28.31
	Fuel poverty %	83,664,247	11.98	3.48	2.3	27.26
	% Non-whites	83,664,247	60.21	11.29	44.3	98.4

Note: Carstairs index is the sum of standardised values from the four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding.

Appendix Table 2
The association between Carstairs index and daily aircraft noise

Only Carstairs index is used; standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1				
Dependent variable:	LAeq24 (00:00–24:00)	Lday (7:00 and 19:00)	Leve (19:00–23:00)	Lnight (23:00–07:00)
Carstairs index Q1 (Reference; least deprived)				
Carstairs index Q2	0.30***	0.22***	−0.22***	2.06***
	(0.04)	(0.04)	(0.04)	(0.04)
Carstairs index Q3	−0.05	−0.09**	−0.95***	1.98***
	(0.04)	(0.04)	(0.04)	(0.04)
Carstairs index Q4	−0.31***	−0.35***	−1.05***	1.73***
	(0.04)	(0.04)	(0.04)	(0.05)
Carstairs index Q5 (most deprived)	−0.08*	−0.20***	−0.79***	2.06***
	(0.04)	(0.04)	(0.04)	(0.05)
Constant (mean Q1 noise levels)	42.74***	44.19***	42.90***	33.44***
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	284,165,204	284,165,204	284,165,204	283,689,925
Number of postcodes	164,012	164,012	164,012	164,012
Autocorrelation	AR1	AR1	AR1	AR1

Note: This table presents results from regression on Equation (1) but only use Carstairs index. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.
The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 3
The association between avoidable death rates and daily aircraft noise

Only avoidable death rates is used; standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1				
Dependent variable:	LAeq24 (00:00–24:00)	Lday (7:00 and 19:00)	Leve (19:00–23:00)	Lnight (23:00–07:00)
Avoidable death Q1 (Reference; lowest rates)				
Avoidable death Q2	0.26***	0.07***	0.54***	0.53***
	(0.00)	(0.00)	(0.00)	(0.00)
Avoidable death Q3	0.45***	0.35***	0.54***	0.39***
	(0.00)	(0.00)	(0.00)	(0.00)
Avoidable death Q4	0.03***	0.06***	0.72***	0.38***
	(0.01)	(0.01)	(0.01)	(0.01)
Avoidable death Q5 (highest rates)	0.64***	0.35***	1.78***	1.17***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant (mean Q1 noise levels)	42.43***	43.92***	41.52***	34.49***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	280,841,749	280,841,749	280,841,749	280,371,968
Number of postcodes	162,029	162,029	162,029	162,029
Autocorrelation	AR1	AR1	AR1	AR1

Note: This table presents results from regression on Equation (1) but only use avoidable death rates. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

Appendix Table 4
The association between fuel poverty and daily aircraft noise

Only fuel poverty is used; standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1				
Dependent variable:	LAeq24 (00:00–24:00)	Lday (7:00 and 19:00)	Leve (19:00–23:00)	Lnight (23:00–07:00)
Fuel poverty Q1 (Reference; lowest)				
Fuel poverty Q2	0.10***	0.02***	0.12***	0.11***
	(0.00)	(0.00)	(0.00)	(0.00)
Fuel poverty Q3	0.09***	0.01***	0.07***	0.14***
	(0.00)	(0.00)	(0.00)	(0.00)
Fuel poverty Q4	0.08***	0.03***	0.07***	0.07***
	(0.00)	(0.00)	(0.00)	(0.00)
Fuel poverty Q5 (highest)	0.01***	−0.01***	−0.05***	−0.09***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant (mean Q1 noise levels)	42.66***	44.09***	42.26***	34.97***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	284,165,204	284,165,204	284,165,204	283,689,925
Number of postcodes	164,012	164,012	164,012	164,012
Autocorrelation	AR1	AR1	AR1	AR1

Note: This table presents results from regression on Equation (1) but only use fuel poverty rates. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

Appendix Table 5
The association between Carstairs index and daily aircraft noise stratified by ethnicity

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
Panel 1:Dependent variable: Lday (7:00 and 19:00)	Carstairs index Q1 (Reference; least deprived)			
	Carstairs index Q2	0.53***	1.77***	2.22***
		(0.05)	(0.08)	(0.21)
	Carstairs index Q3	0.02	2.80***	2.76***
		(0.06)	(0.07)	(0.19)
	Carstairs index Q4	-0.86***	2.43***	4.17***
		(0.10)	(0.08)	(0.18)
	Carstairs index Q5 (most deprived)	-0.63**	2.74***	4.40***
		(0.31)	(0.09)	(0.18)
	Constant (mean Q1 noise levels)	44.79***	41.60***	39.46***
		(0.03)	(0.07)	(0.18)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499
Panel 2:Dependent variable: Leve (19:00 – 23:00)	Carstairs index Q1 (Reference; least deprived)			
	Carstairs index Q2	0.01	0.99***	1.72***
		(0.05)	(0.08)	(0.21)
	Carstairs index Q3	-1.25***	1.51***	1.85***
		(0.06)	(0.07)	(0.19)
	Carstairs index Q4	-1.63***	1.09***	3.19***

(continued on next page)

Appendix Table 5 (*continued*)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
		(0.10)	(0.07)	(0.18)
	Carstairs index Q5 (most deprived)	-0.83***	1.44***	3.48***
		(0.30)	(0.09)	(0.18)
	Constant (mean Q1 noise levels)	43.52***	40.81***	38.50***
		(0.03)	(0.07)	(0.17)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499
Panel 3:Dependent variable: Lnight (23:00 – 07:00)	Carstairs index Q1 (Reference; least deprived)			
	Carstairs index Q2	2.48***	2.46***	2.50***
		(0.06)	(0.09)	(0.23)
	Carstairs index Q3	1.97***	3.65***	3.29***
		(0.07)	(0.08)	(0.21)
	Carstairs index Q4	1.11***	3.15***	5.13***
		(0.12)	(0.08)	(0.20)
	Carstairs index Q5 (most deprived)	0.52	3.47***	5.80***
		(0.36)	(0.10)	(0.20)
	Constant (mean Q1 noise levels)	33.63***	32.50***	29.71***
		(0.04)	(0.07)	(0.20)
	Observations	104,000,584	96,165,738	83,523,603
	Number of postcodes	60,084	55,429	48,499
Panel 4:Dependent variable: LAeq24 (00:00 -24:00)	Carstairs index Q1 (Reference; least deprived)			
	Carstairs index Q2	0.64***	1.72***	2.18***
		(0.05)	(0.08)	(0.21)
	Carstairs index Q3	0.02	2.75***	2.68***
		(0.06)	(0.08)	(0.19)
	Carstairs index Q4	-0.83***	2.36***	4.20***
		(0.10)	(0.08)	(0.19)
	Carstairs index Q5 (most deprived)	-0.59*	2.71***	4.57***
		(0.31)	(0.09)	(0.18)
	Constant (mean Q1 noise levels)	43.35***	40.28***	37.97***
		(0.03)	(0.07)	(0.18)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499

Note: This table presents results from regression on Equation (1) while stratifying samples by % non-whites. The deprivation used is Carstairs index. The dependent variables were LAeq24, Lday, Leve and Lnight in Panel (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.
The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 6
The association between Avoidable death rates and daily aircraft noise stratified by ethnicity

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
Panel 1:Dependent variable: Lday (7:00 and 19:00)	Avoidable death Q1 (Reference; lowest rates)			
	Avoidable death Q2	-0.04***	0.02***	0.50***
		(0.00)	(0.01)	(0.01)
	Avoidable death Q3	0.12***	0.41***	0.95***
		(0.01)	(0.01)	(0.01)
	Avoidable death Q4	0.12***	0.45***	0.74***
		(0.04)	(0.02)	(0.02)
	Avoidable death Q5 (highest rates)	0.56***	0.88***	0.73***
		(0.04)	(0.02)	(0.02)
	Constant (mean Q1 noise levels)	44.82***	43.38***	42.66***
		(0.02)	(0.02)	(0.03)
	Observations	102,778,726	94,404,248	83,658,775
	Number of postcodes	59,272	54,261	48,496
Panel 2:Dependent variable: Leve (19:00 – 23:00)	Avoidable death Q1 (Reference; lowest rates)			
	Avoidable death Q2	0.41***	0.56***	1.09***
		(0.00)	(0.01)	(0.01)
	Avoidable death Q3	0.22***	0.78***	1.46***
		(0.01)	(0.01)	(0.01)

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Appendix Table 6 (*continued*)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
	Avoidable death Q4	-0.68***	1.05***	1.92***
		(0.04)	(0.02)	(0.01)
	Avoidable death Q5 (highest rates)	0.95***	2.20***	2.32***
		(0.04)	(0.02)	(0.02)
	Constant (mean Q1 noise levels)	43.09***	40.89***	39.70***
		(0.02)	(0.02)	(0.03)
	Observations	102,778,726	94,404,248	83,658,775
	Number of postcodes	59,272	54,261	48,496
Panel 3:Dependent variable: Lnight (23:00 – 07:00)	Avoidable death Q1 (Reference; lowest rates)			
	Avoidable death Q2	0.39***	0.47***	0.91***
		(0.01)	(0.01)	(0.01)
	Avoidable death Q3	0.21***	0.38***	1.02***
		(0.01)	(0.01)	(0.01)
	Avoidable death Q4	1.99***	0.24***	0.93***
		(0.05)	(0.02)	(0.01)
	Avoidable death Q5 (highest rates)	3.17***	1.15***	1.03***
		(0.05)	(0.02)	(0.02)
	Constant (mean Q1 noise levels)	33.96***	34.99***	33.77***
		(0.03)	(0.02)	(0.03)
	Observations	102,607,131	94,246,697	83,518,140
	Number of postcodes	59,272	54,261	48,496
Panel 4:Dependent variable: LAeq24 (00:00 -24:00)	Avoidable death Q1 (Reference; lowest rates)			
	Avoidable death Q2	0.12***	0.01***	0.16***
		(0.00)	(0.00)	(0.01)
	Avoidable death Q3	0.09***	0.02***	0.13***
		(0.00)	(0.00)	(0.01)
	Avoidable death Q4	0.10***	-0.02***	0.15***
		(0.00)	(0.00)	(0.01)
	Avoidable death Q5 (highest rates)	0.08***	0.01	-0.03***
		(0.00)	(0.00)	(0.01)
	Constant (mean Q1 noise levels)	43.47***	42.49***	41.87***
		(0.02)	(0.02)	(0.03)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499

Note: This table presents results from regression on Equation (1) while stratifying samples by % non-whites. The deprivation used is avoidable death rates. The dependent variables were LAeq24, Lday, Leve and Lnight in Panel (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

Appendix Table 7

The association between fuel poverty and daily aircraft noise stratified by ethnicity

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
Panel 1:Dependent variable: Lday (7:00 and 19:00)	Fuel poverty Q1 (Reference; lowest rates)			
	Fuel poverty Q2	0.01***	-0.01*	0.13***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q3	-0.04***	0.00	0.14***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q4	0.01**	-0.01***	0.18***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q5 (highest rates)	0.02***	0.03***	0.03***
		(0.01)	(0.01)	(0.01)
	Constant (mean Q1 noise levels)	44.92***	43.87***	43.26***
		(0.02)	(0.02)	(0.03)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499
Panel 2:Dependent variable: Leve (19:00 – 23:00)	Fuel poverty Q1 (Reference; lowest rates)			
	Fuel poverty Q2	0.11***	0.04***	0.25***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q3	0.03***	0.01***	0.20***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q4	-0.01**	0.02***	0.24***

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Appendix Table 7 (*continued*)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data stratified by:		% Non-whites T1 (lowest concentration of non-whites)	% Non-whites T2	% Non-whites T3 (highest concentration of non-whites)
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q5 (highest rates)	-0.01**	-0.02***	0.01
		(0.01)	(0.00)	(0.01)
	Constant (mean Q1 noise levels)	43.21***	41.97***	41.36***
		(0.02)	(0.02)	(0.03)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499
Panel 3:Dependent variable: Lnight (23:00 – 07:00)	Fuel poverty Q1 (Reference; lowest rates)			
	Fuel poverty Q2	0.17***	0.00	0.12***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q3	0.24***	-0.00	0.06***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q4	0.13***	-0.08***	-0.02***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q5 (highest rates)	-0.23***	-0.17***	-0.25***
		(0.01)	(0.01)	(0.01)
	Constant (mean Q1 noise levels)	34.81***	35.53***	34.71***
		(0.02)	(0.02)	(0.03)
	Observations	104,000,584	96,165,738	83,523,603
	Number of postcodes	60,084	55,429	48,499
Panel 4:Dependent variable: LAeq24 (00:00 -24:00)	Fuel poverty Q1 (Reference; lowest rates)			
	Fuel poverty Q2	0.12***	0.01***	0.16***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q3	0.09***	0.02***	0.13***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q4	0.10***	-0.02***	0.15***
		(0.00)	(0.00)	(0.01)
	Fuel poverty Q5 (highest rates)	0.08***	0.01	-0.03***
		(0.00)	(0.00)	(0.01)
	Constant (mean Q1 noise levels)	43.47***	42.49***	41.87***
		(0.02)	(0.02)	(0.03)
	Observations	104,174,488	96,326,469	83,664,247
	Number of postcodes	60,084	55,429	48,499

Note: This table presents results from regression on Equation (1) while stratifying samples by % non-whites. The deprivation used is Fuel poverty rates. The dependent variables were LAeq24, Lday, Leve and Lnight in Panel (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

Appendix Table 8

The association between deprivation measures and daily LAeq24 aircraft noise stratified by year

Noise metric: LAeq24 (00:00 -24:00)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data stratified by:	2014	2015	2016	2017	2018	
Panel 1:Deprivation measure: Carstairs index	Carstairs index Q1 (Reference; least deprived)					
	Carstairs index Q2	0.26***	0.28***	0.23***	0.40***	0.34***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q3	0.04	-0.01	-0.17***	0.05	-0.01
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q4	-0.27***	-0.32***	-0.42***	-0.20***	-0.25***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q5 (most deprived)	-0.36***	-0.24***	-0.19***	0.15***	0.12***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	43.08***	42.70***	41.90***	41.53***	41.42***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671
Panel 2:Deprivation measure: avoidable death	Avoidable death Q1 (Reference; lowest rates)					
	Avoidable death Q2	0.32***	-3.96***	4.49***	3.62***	3.27***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Avoidable death Q3	-0.56***	-2.41***	2.01***	2.54***	2.51***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Avoidable death Q4	0.88***	-0.81***	3.69***	3.92***	4.79***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Avoidable death Q5 (highest rates)	1.21***	-0.02	5.17***	5.86***	5.57***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	42.61***	43.99***	38.40***	37.96***	37.83***
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)

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Appendix Table 8 (*continued*)

Noise metric: LAeq24 (00:00 -24:00)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data stratified by:	2014	2015	2016	2017	2018	
	Observations	56,367,315	56,238,470	56,268,108	55,940,612	56,027,244
	Number of postcodes	154,431	154,078	153,738	153,683	153,921
Panel 3:Deprivation measure: fuel poverty rates	Fuel poverty Q1 (Reference; lowest rates)					
	Fuel poverty Q2	-0.42***	0.09**	-1.40***	-0.58***	0.47***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q3	-0.52***	-0.11***	-2.16***	-0.46***	0.28***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q4	-0.28***	-0.24***	-2.21***	-1.48***	-0.61***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q5 (highest rates)	-0.42***	-0.86***	-3.19***	-2.47***	-1.44***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	43.34***	42.86***	43.49***	42.55***	41.70***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671

Note: This table presents results from regression on Equation (1) while stratifying samples by year (2014–2018). The deprivation used is Carstairs index in Panel 1, avoidable death rates in Panel 2, and fuel poverty rates in Panel 3. The dependent variable was LAeq24. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.

The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 9

The association between deprivation measures and daily Lday aircraft noise stratified by year

Noise metric: Lday (7:00 and 19:00)

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Data stratified by:	2014	2015	2016	2017	2018	
Panel 1:Deprivation measure: Carstairs index	Carstairs index Q1 (Reference; least deprived)					
	Carstairs index Q2	0.25***	0.23***	0.18***	0.23***	0.17***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q3	0.07**	-0.02	-0.17***	-0.10**	-0.15***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q4	-0.25***	-0.35***	-0.42***	-0.31***	-0.37***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q5 (most deprived)	-0.40***	-0.32***	-0.25***	-0.04	-0.18***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	44.39***	44.06***	43.23***	42.87***	42.58***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671
Panel 2:Deprivation measure: avoidable death	Avoidable death Q1 (Reference; lowest rates)					
	Avoidable death Q2	0.27***	-3.81***	4.41***	3.31***	2.62***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Avoidable death Q3	-0.70***	-2.38***	1.87***	2.46***	2.26***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Avoidable death Q4	0.75***	-0.80***	3.61***	3.75***	4.23***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Avoidable death Q5 (highest rates)	0.94***	-0.17***	4.96***	5.19***	4.59***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	44.05***	45.31***	39.82***	39.47***	39.40***
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
	Observations	56,367,315	56,238,470	56,268,108	55,940,612	56,027,244
	Number of postcodes	154,431	154,078	153,738	153,683	153,921
Panel 3:Deprivation measure: fuel poverty rates	Fuel poverty Q1 (Reference; lowest rates)					
	Fuel poverty Q2	-0.44***	0.14***	-1.40***	-0.71***	0.04
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q3	-0.57***	-0.09**	-2.18***	-0.54***	-0.05
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q4	-0.26***	-0.19***	-2.21***	-1.49***	-0.85***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q5 (highest rates)	-0.44***	-0.77***	-3.13***	-2.30***	-1.56***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	44.67***	44.15***	44.79***	43.78***	42.93***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671

Note: This table presents results from regression on Equation (1) while stratifying samples by year (2014–2018). The deprivation used is Carstairs index in Panel 1, avoidable death rates in Panel 2, and fuel poverty rates in Panel 3. The dependent variable was LAeq24. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.

The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 10
The association between deprivation measures and daily Leve aircraft noise stratified by year

Noise metric: Leve (19:00 – 23:00)						
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1						
Data stratified by:	2014	2015	2016	2017	2018	
Panel 1:Deprivation measure: Carstairs index	Carstairs index Q1 (Reference; least deprived)					
	Carstairs index Q2	-0.24***	-0.13***	-0.07	-0.01	0.14***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q3	-0.82***	-0.74***	-0.65***	-0.56***	-0.41***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q4	-0.93***	-0.89***	-0.84***	-0.81***	-0.66***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Carstairs index Q5 (most deprived)	-0.97***	-0.81***	-0.60***	-0.60***	-0.30***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	43.18***	42.58***	41.85***	42.14***	41.77***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671
Panel 2:Deprivation measure: avoidable death	Avoidable death Q1 (Reference; lowest rates)					
	Avoidable death Q2	0.32***	-3.60***	3.99***	3.05***	3.86***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Avoidable death Q3	-0.41***	-2.32***	1.81***	2.31***	2.72***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Avoidable death Q4	0.56***	-1.12***	3.15***	3.12***	5.34***
		(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
	Avoidable death Q5 (highest rates)	0.75***	-0.33***	4.62***	4.64***	5.87***
		(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	42.34***	43.51***	38.44***	38.77***	37.53***
		(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
	Observations	56,367,315	56,238,470	56,268,108	55,940,612	56,027,244
	Number of postcodes	154,431	154,078	153,738	153,683	153,921
Panel 3:Deprivation measure: fuel poverty rates	Fuel poverty Q1 (Reference; lowest rates)					
	Fuel poverty Q2	-0.63***	0.01	-1.11***	-0.69***	0.35***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q3	-0.47***	-0.27***	-1.88***	-0.76***	-0.25***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q4	-0.63***	-0.57***	-1.96***	-1.65***	-1.12***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Fuel poverty Q5 (highest rates)	-0.78***	-1.01***	-2.98***	-2.70***	-2.04***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Constant (mean Q1 noise levels)	43.08***	42.43***	42.92***	42.83***	42.10***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	57,058,260	56,925,400	56,934,228	56,583,072	56,664,244
	Number of postcodes	156,324	155,960	155,558	155,448	155,671

Note: This table presents results from regression on Equation (1) while stratifying samples by year (2014–2018). The deprivation used is Carstairs index in Panel 1, avoidable death rates in Panel 2, and fuel poverty rates in Panel 3. The dependent variable was LAeq24. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.

The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 11
The association between deprivation measures and daily Lnight aircraft noise stratified by year

Noise metric: Lnight (23:00 – 07:00)						
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1						
Data stratified by:	2014	2015	2016	2017	2018	
Panel 1:Deprivation measure: Carstairs index	Carstairs index Q1 (Reference; least deprived)					
	Carstairs index Q2	1.65***	2.19***	1.80***	2.68***	1.96***
		(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
	Carstairs index Q3	1.51***	2.19***	1.62***	2.77***	1.94***
		(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
	Carstairs index Q4	1.23***	1.93***	1.39***	2.53***	1.64***
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
	Carstairs index Q5 (most deprived)	1.14***	2.18***	1.67***	2.97***	2.14***
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	34.03***	34.88***	32.63***	31.55***	33.69***
		(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
	Observations	56,901,936	56,923,663	56,932,197	56,425,589	56,506,540
	Number of postcodes	156,324	155,960	155,558	155,448	155,671
Panel 2:Deprivation measure: avoidable death	Avoidable death Q1 (Reference; lowest rates)					

(continued on next page)

Appendix Table 11 (*continued*)

Noise metric: Lnight (23:00 – 07:00)						
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1						
Data stratified by:	2014	2015	2016	2017	2018	
	Avoidable death Q2	1.30***	-3.88***	5.89***	6.84***	5.87***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Avoidable death Q3	1.58***	-0.58***	4.38***	4.91***	3.74***
		(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
	Avoidable death Q4	3.27***	1.51***	6.23***	7.35***	7.38***
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
	Avoidable death Q5 (highest rates)	3.53***	2.33***	7.66***	10.27***	8.54***
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	32.90***	36.30***	28.51***	26.98***	29.43***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Observations	56,212,884	56,236,768	56,266,094	55,784,910	55,871,312
	Number of postcodes	154,431	154,078	153,738	153,683	153,921
Panel 3:Deprivation measure: fuel poverty rates	Fuel poverty Q1 (Reference; lowest rates)					
	Fuel poverty Q2	0.28***	0.27***	-1.57***	1.07***	2.85***
		(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
	Fuel poverty Q3	0.68***	0.69***	-2.08***	1.47***	3.04***
		(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
	Fuel poverty Q4	0.97***	0.67***	-1.86***	0.58***	2.08***
		(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
	Fuel poverty Q5 (highest rates)	0.89***	-0.08*	-2.86***	-0.92***	0.88***
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
	Constant (mean Q1 noise levels)	34.60***	36.28***	35.53***	33.28***	33.47***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	Observations	56,901,936	56,923,663	56,932,197	56,425,589	56,506,540
	Number of postcodes	156,324	155,960	155,558	155,448	155,671

Note: This table presents results from regression on Equation (1) while stratifying samples by year (2014–2018). The deprivation used is Carstairs index in Panel 1, avoidable death rates in Panel 2, and fuel poverty rates in Panel 3. The dependent variable was LAeq24. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.
The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 12
The association between Carstairs index (as a continuous variable) and daily aircraft noise

Only Carstairs index (as a continuous variable) is used; standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1				
Dependent variable:	Lday (7:00 and 19:00)	Leve (19:00–23:00)	Lnight (23:00–07:00)	LAeq24 (00:00–24:00)
Carstairs index	−0.04***	−0.10***	0.16***	−0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	44.14***	42.39***	34.86***	42.74***
	(0.01)	(0.01)	(0.02)	(0.01)
Observations	284,165,204	284,165,204	283,689,925	284,165,204
Number of postcodes	164,012	164,012	164,012	164,012
Autocorrelation	AR1	AR1	AR1	AR1

Note: This table presents results from regression on Equation (1) but only use Carstairs index as a continuous variable. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.
The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.

Appendix Table 13
The association between avoidable death rates (as a continuous variable) and daily aircraft noise

Only avoidable death rates (as a continuous variable) is used; standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				
Dependent variable:	Lday (7:00 and 19:00)	Leve (19:00 – 23:00)	Lnight (23:00 – 07:00)	LAeq24 (00:00 -24:00)
Avoidable death rates	0.00***	0.00***	-0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	44.00***	41.66***	36.86***	43.04***
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	280,841,749	280,841,749	280,371,968	280,841,749
Number of postcodes	162,029	162,029	162,029	162,029
Autocorrelation	AR1	AR1	AR1	AR1

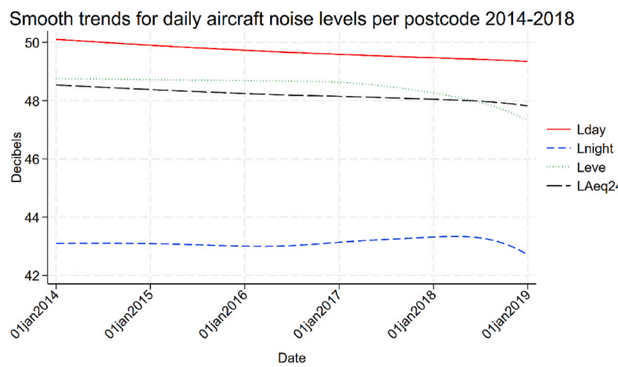
Note: This table presents results from regression on Equation (1) but only use avoidable death rates as a continuous variable. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

Appendix Table 14
The association between fuel poverty (as a continuous variable) and daily aircraft noise

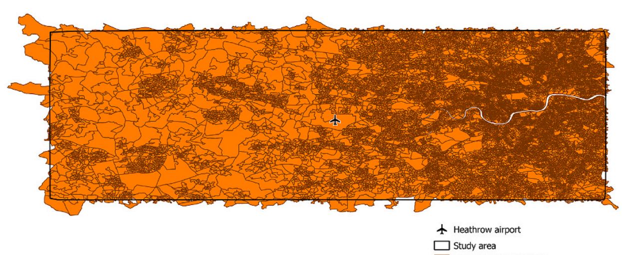
Only fuel poverty (as a continuous variable) is used; standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1				
Dependent variable:	Lday (7:00 and 19:00)	Leve (19:00–23:00)	Lnight (23:00–07:00)	LAeq24 (00:00–24:00)
Fuel poverty	0.01***	−0.00***	−0.02***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	44.03***	42.32***	35.19***	42.65***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	284,165,204	284,165,204	283,689,925	284,165,204
Number of postcodes	164,012	164,012	164,012	164,012
Autocorrelation	AR1	AR1	AR1	AR1

Note: This table presents results from regression on Equation (1) but only use fuel poverty as a continuous variable. The dependent variables were LAeq24, Lday, Leve and Lnight in Column (1), (2), (3) and (4). The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months and years.

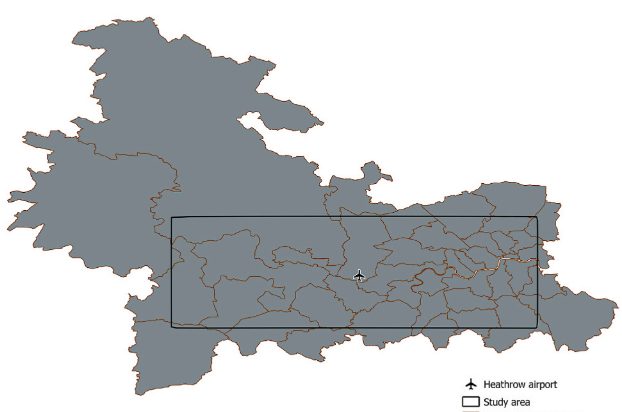
Appendix. Figures



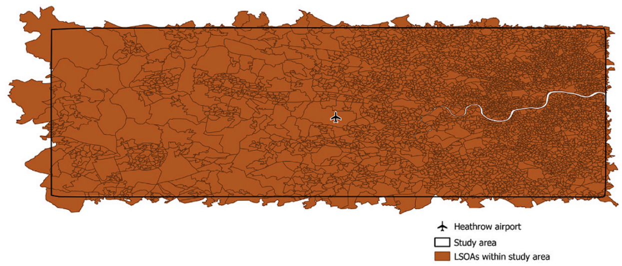
Appendix Fig. 1. Average daily aircraft noise per postcode in study area by year from 2014 to 2018 (Unit: decibel).Note: A Lowess (Locally Weighted Scatterplot Smoothing) approach is used to plot the smooth trends for aircraft noise levels per postcode from 2014 to 2018.



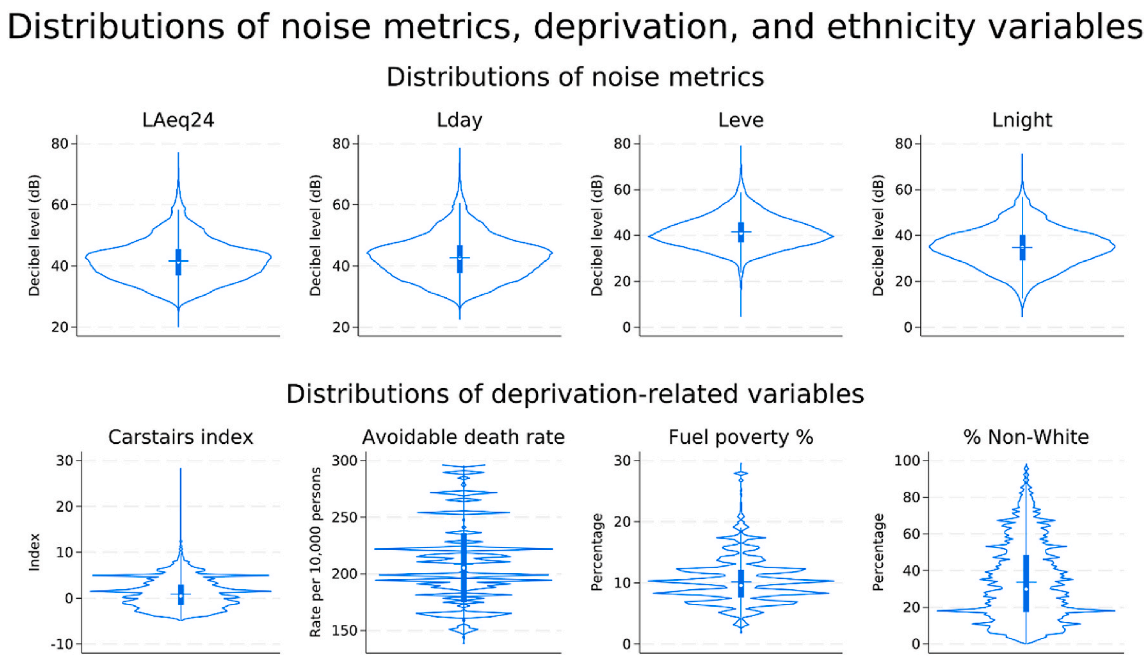
Appendix Fig. 2(a). All Census Output Areas included in the computation of quitiles of Carstairs index and tertiles of % non-white population (any COA with some area within the study area was included).



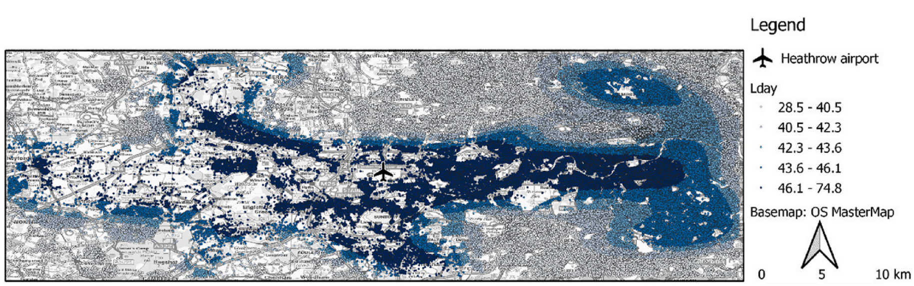
Appendix Fig. 2(b). All Local Authority Districts (LADs) included in the computation of quitiles of avoidable death rates (any LAD with some area within the study area was included).



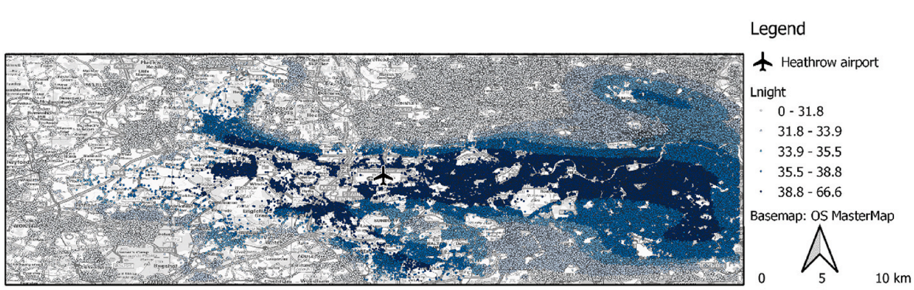
Appendix Fig. 2(c). All Lower Layer Super Output Areas (SOAs included in the computation of quitiles of fuel poverty rates (any SOA with some area within the study area was included).



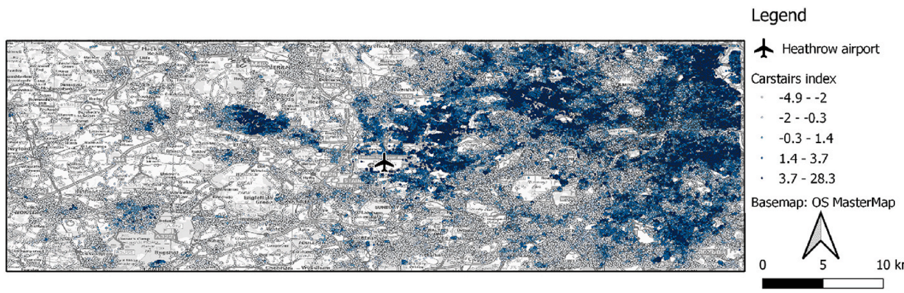
Appendix Fig. 3. Distributions of noise metrics, deprivation, and ethnicity variables.Note: The violin plots visualise the spread of data for various noise metrics (LAeq24, Lday, Leve, Lnight) and socio-economic indicators (Carstairs index, avoidable death rates, fuel poverty %, % Non-White) across postcodes. The bar inside each plot represents the median, while the line indicates the mean.The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.



Appendix Fig. 4(a) Lday noise levels (2014 annual average) for each postcode included in study (Unit: decibel).

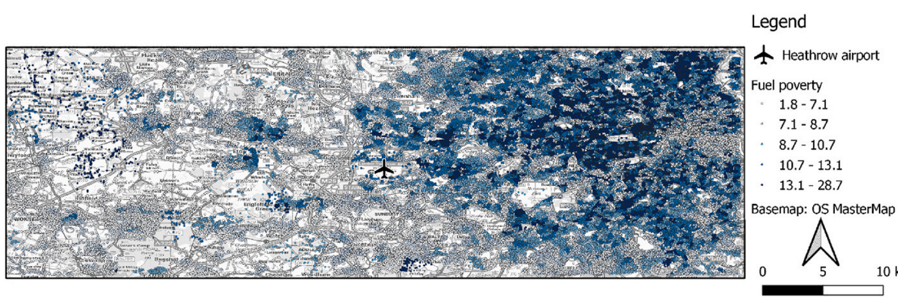


Appendix Fig. 4(b). Lnight noise levels (2014 annual average) for each postcode included in study (Unit: decibel).Note: this figure presents the 2014 yearly averaged Lnight noise level for each postcode included in study.

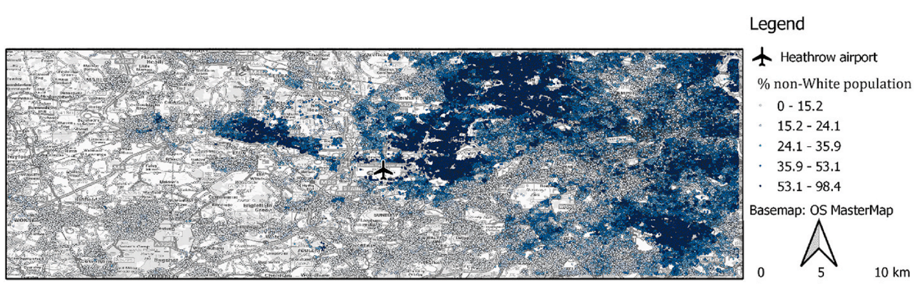


Appendix Fig. 4(c). Carstairs index (2011) for each postcode included in study (Unit: unitless).Note: this figure presents the 2011 yearly Carstairs index for each postcode included in study. Carstairs index is the sum of standardised values from the four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding.

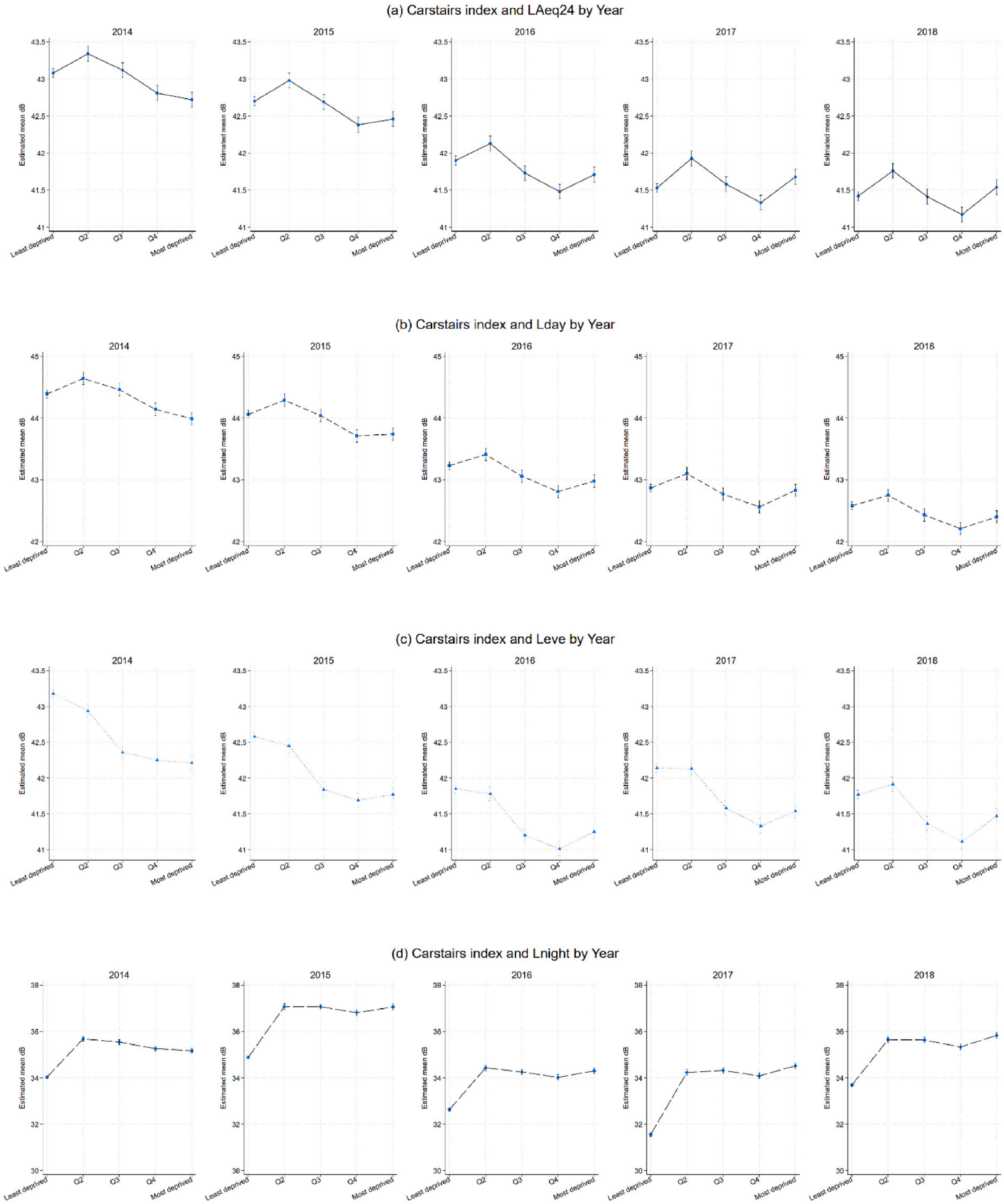
Appendix Fig. 4(d). Avoidable death rates (2014) for each postcode included in study (Unit: deaths per 100,000 persons).Note: this figure presents the 2014 yearly avoidable death rates for each postcode included in study.



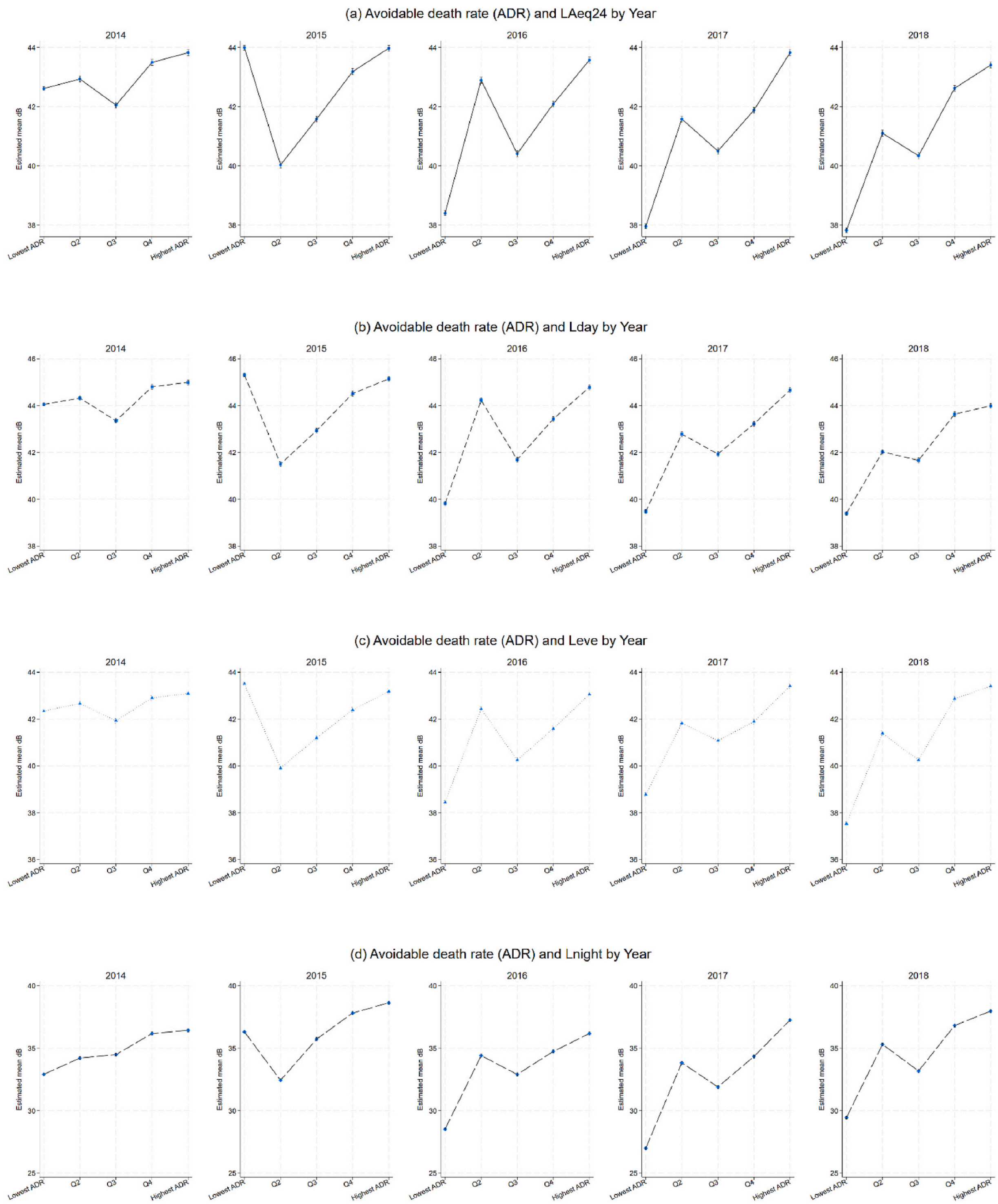
Appendix Fig. 4(e). Fuel poverty rates (2014) for each postcode included in study (Unit: fuel poor households per 100 households).Note: this figure presents the 2014 yearly fuel poverty rates for each postcode included in study.



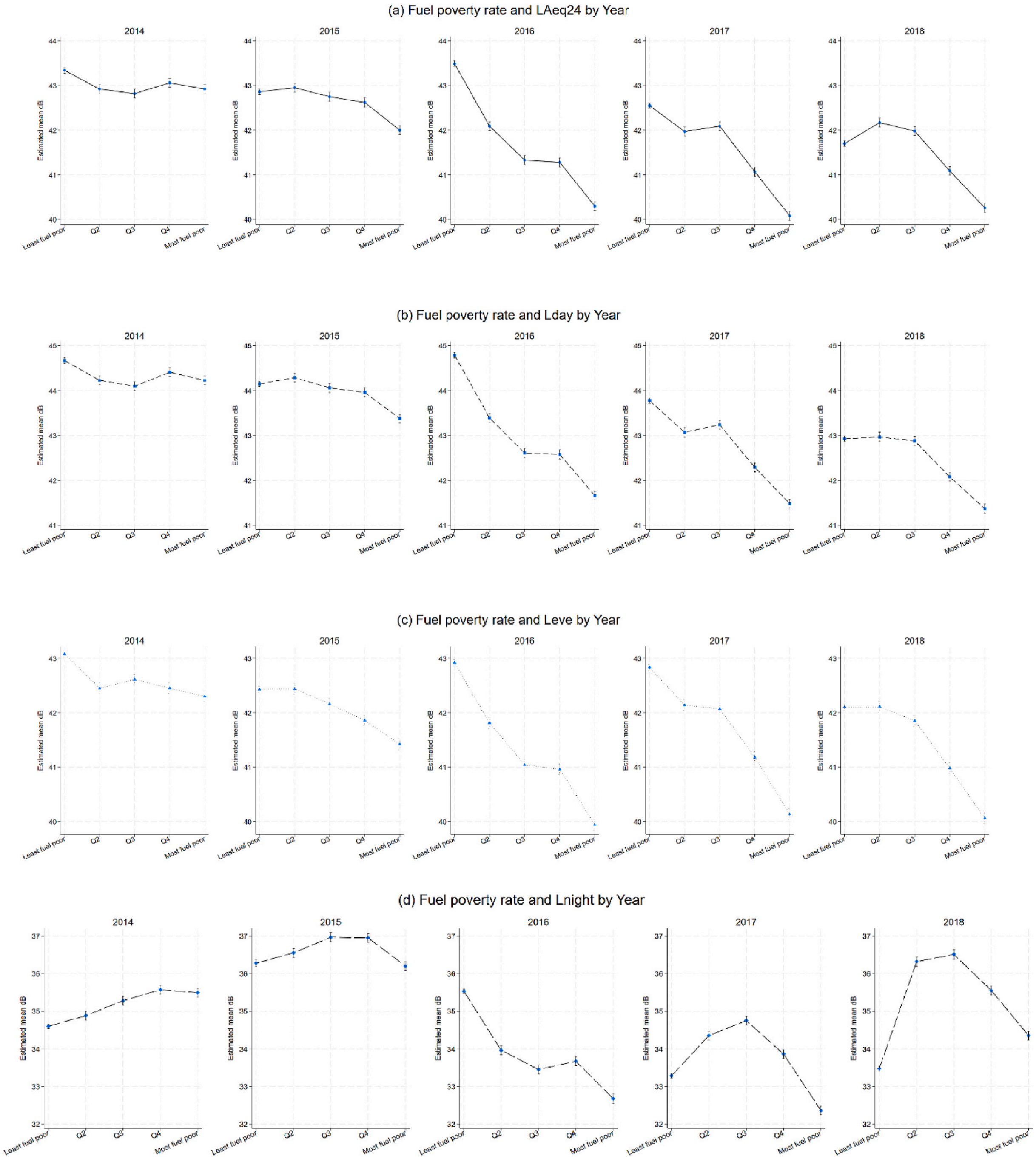
Appendix Fig. 4(f). % non-White population (2011) for each postcode included in study.Note: this figure presents the 2011 yearly % non-White population for each postcode included in study.



Appendix Fig. 5. The association between Carstairs index and daily aircraft noise stratified by year.Note: This table presents results from regression on Equation 1 while stratifying samples by year (2014–2018). The deprivation used is Carstairs index. The noise metrics were LAeq24, Lday, Leve and Lnight in (a), (b), (c), and (d), respectively. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months. The Carstairs index is derived from four variables: male unemployment, low social class, households without vehicle ownership, and overcrowding. Lower scores indicate less deprivation, while higher scores represent greater deprivation.



Appendix Fig. 6. The association between avoidable death rate and daily aircraft noise stratified by year.Note: This table presents results from regression on Equation 1 while stratifying samples by year (2014–2018). The deprivation used is avoidable death rate. The noise metrics were LAeq24, Lday, Leve and Lnight in (a), (b), (c), and (d), respectively. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.



Appendix Fig. 7. The association between fuel poverty rate and daily aircraft noise stratified by year.Note: This table presents results from regression on Equation (1) while stratifying samples by year (2014–2018). The deprivation used is fuel poverty rate. The noise metrics were LAeq24, Lday, Leve and Lnight in (a), (b), (c), and (d), respectively. The regression method is Random-Effects with AR(1) disturbance. All models have controlled for months.

Data availability

Data will be made available on request.

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