Socioeconomic and ethnic inequalities in exposure to air and noise pollution in London

Cathryn Tonne[1], Carles Milà[1], Daniela Fecht[2], Mar Alvarez[1], John Gulliver[2], James Smith[3], Sean Beevers[3], H Ross Anderson[3,4], Frank Kelly[3]

[1] ISGlobal, Universitat Pompeu Fabra, CIBER Epidemiología y Salud Pública, Barcelona, Spain

[2] UK Small Area Health Statistics Unit, MRC-PHE Centre for Environment and Health, Imperial College London, London, UK

[3] Environmental Research Group, MRC-PHE Centre for Environment and Health, King's College London, London, UK

[4] Population Health Research Institute, St George´s, University of London

Corresponding author:

Cathryn Tonne

Cathryn.tonne@isglobal.org

+34 93 214 7361

ISGlobal

Doctor Aiguader, 88

08003 Barcelona

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Abstract

Background: Transport-related air and noise pollution, exposures linked to adverse health outcomes, varies within cities potentially resulting in exposure inequalities. Relatively little is known regarding inequalities in personal exposure to air pollution or transport-related noise.

Objectives: Our objectives were to quantify socioeconomic and ethnic inequalities in London in 1) air pollution exposure at residence compared to personal exposure; and 2) transport-related noise at residence from different sources.

Methods: We used individual-level data from the London Travel Demand Survey (n=45,079) between 2006-2010. We modeled residential (CMAQ-urban) and personal (London Hybrid Exposure Model) particulate matter <2.5 microns and nitrogen dioxide (NO_2), road-traffic noise at residence (TRANEX) and identified those within 50dB noise contours of railways and Heathrow airport. We analyzed relationships between household income, area-level income deprivation and ethnicity with air and noise pollution using quantile and logistic regression.

Results: We observed inverse patterns in inequalities in air pollution when estimated at residence versus personal exposure with respect to household income (categorical, 8 groups). Compared to the lowest income group (< £10,000), the highest group (>£75,000) had lower residential NO_2 (-1.3 (95% CI -2.1, -0.6) $\mu g/m^3$ in the 95th exposure quantile) but higher personal NO_2 exposure (1.9 (95% CI 1.6, 2.3) $\mu g/m^3$ in the 95th quantile), which was driven largely by transport mode and duration. Inequalities in residential exposure to NO_2 with respect to area-level deprivation were larger at lower exposure quantiles (e.g. estimate for NO_2 5.1 (95% CI 4.6, 5.5) at quantile 0.15 versus 1.9 (95% CI 1.1, 2.6) at quantile 0.95), reflecting low-deprivation, high residential NO_2 areas in the city centre. Air pollution exposure at residence consistently overestimated personal exposure; this overestimation varied with age, household income, and area-level income deprivation. Inequalities in road traffic noise were generally small. In logistic regression models, the odds of living within a 50dB contour of aircraft noise were highest in individuals with the highest household income, white ethnicity, and with the lowest area-level income deprivation. Odds of living within a 50dB contour of rail noise were 19% (95% CI 3, 37) higher for black compared to white individuals.

Conclusions: Socioeconomic inequalities in air pollution exposure were different for modeled residential versus personal exposure, which has important implications for environmental justice and confounding in epidemiology studies. Exposure misclassification was dependent on several factors related to health, a potential source of bias in epidemiological studies. Quantile regression revealed that socioeconomic and ethnic inequalities in air pollution are often not uniform across the exposure distribution.

Introduction

Transport-related air and noise pollution, environmental exposures linked to a range of adverse health outcomes,(Health Effects Institute, 2009; WHO Europe, 2011) varies within cities. This variation may result in exposure inequalities: different socioeconomic and ethnic groups being more exposed than others.(European Commission, 2016) Socioeconomic and ethnic inequalities in health are well established.(Shiels et al., 2017; Stringhini et al., 2017) The unequal distribution of environmental exposures may contribute to these health inequalities where exposures are higher in individuals or communities with lower socioeconomic position or in specific ethnic groups.

Studies from the US show a fairly consistent relationship between individuals or communities of lower socioeconomic position and increased exposure to air pollution.(Hajat et al., 2015) Evidence from Europe is mixed,(Temam et al., 2017) with some studies indicating non-linear relationships or high exposures in city centres with concentrations of individuals with high socioeconomic position.(Goodman et al., 2011; Havard et al., 2009) Within Europe, areas with a high proportion of non-white residents have also been observed to have higher air pollution exposures.(Fecht et al., 2015) However, nearly all studies have considered exposure inequalities based on residential exposures, with very few examples based on personal exposure,(Jantunen et al., 2000; Rotko et al., 2001) or exposures experienced during commuting.(Rivas et al., 2017) In addition, most studies have investigated environmental inequalities at the neighborhood or area-level, while few have investigated exposure inequalities using individual-level socioeconomic or ethnicity data.(Hajat et al., 2015; Temam et al., 2017)

Compared to air pollution, fewer studies have investigated inequalities in transport-related noise and most have focused on road-traffic, rather than rail or aircraft noise.(European Commission, 2016) The available evidence is inconsistent. Several studies have observed positive associations between road-traffic noise and deprivation;(Dale et al., 2015; Havard et al., 2009; Nega et al., 2013) while others have observed the reverse,(Havard et al., 2011) or no association.(Halonen et al., 2015) A small number of studies in Europe have investigated the relationship between different metrics of deprivation and aircraft noise.(Huss et al., 2010; Pelletier et al., 2013). A recent small-area study reported inequalities in environmental noise according to area-level race, racial segregation, and socioeconomic characteristics across the US, but did not differentiate between anthropogenic sources.(Casey et al., 2017)

We aim to fill this gap in the literature by considering air pollution exposure inequalities both at residence and using modeled personal exposure as well as noise exposures from multiple sources. Our objectives were to quantify socioeconomic and ethnic inequalities in 1) air pollution exposure at residence compared to personal exposure; and 2) transport-related noise at residence from different sources. Rather than focus only on inequalities in mean exposures, we consider inequalities across the full exposure distribution, providing a more complete picture of inequalities in transport-related environmental exposures than previous studies.

Methods

Study population The study population was based on individuals who responded to the London Travel Demand Survey (LTDS), conducted by Transport for London to capture data on travel patterns and modal share.(Transport for London, 2015) The survey sampled approximately 8,000 households per year on a rolling basis and was based on a random sample of households. Data were collected through a face-to-face interview in participants' homes. Respondents were asked about their activities on the previous day and how typical this was of their normal day. Transport for London adjusted the sample for sampling weights and non-response to generate a sample representative of London overall as well as sub-regions of the city. We used LTDS data from 45,079 individuals (20,542 households) who responded to the survey between years 2006-2010, after excluding 4,969 individuals (11%) with missing residential postcode, demographic or trip (origin or destination) data (**S Table 1**).

Air pollution data The London Hybrid Exposure Model (LHEM) was used to estimate exposure to air pollution (particulate matter <2.5 microns [$PM_{2.5}$], nitrogen dioxide [NO_2]) of individuals included in the LTDS based on their residential location, trips, mode of transport, and time spent in non-residential locations between trips.

The model is described in detail elsewhere.(Smith et al., 2016) Briefly, trip start and end coordinates, times of trips, and transport mode are taken from the LTDS. The route between origin and destination was simulated using methods appropriate for each travel mode. Exposure to outdoor air pollution was estimated using the Community Multiscale Air Quality Modeling System (CMAQ-urban), described below.(Beevers et al., 2012) To account for penetration of outdoor air indoors, in-building exposures were estimated by applying indoor/outdoor ratios for domestic buildings estimated for each London postcode to the CMAQ-urban estimates.(Taylor et al., 2014) In-vehicle exposures were estimated in LHEM using mass-balance equations. Microenvironmental exposures for trips on the London Underground were estimated based on measured concentrations in the London or Paris metro system. Exposures while walking and cycling were estimated based on the CMAQ-urban estimates for the time and location of the trip. Although the model does not fully capture personal exposure from all sources in all microenvironments, for ease of interpretability, we refer to LHEM as an estimate of personal exposure to ambient pollution.

We used CMAQ-urban to predict ambient air pollution concentrations at place of residence. CMAQ-urban couples the Weather Research and Forecasting meteorological model with the Atmospheric Dispersion Modeling System roads model. We generated annual average concentrations of $PM_{2.5}$ and NO_2 for each hour of the day for the year 2011 at 20m x 20m resolution.(Taylor et al., 2014) Residential air pollution estimates are based on the 24hr mean concentration (**S-Figure 1**).

Road traffic noise Annual road traffic noise for years 2003-10 was modeled at the geometric centroid for all ~190,000 London postcodes using the TRAffic Noise EXposure (TRANEX) model.(Gulliver et al., 2015) Briefly, the model uses detailed information on traffic flows and speeds for each year, land cover, and heights of individual buildings. We used $L_{Aeq,24hr}$ (average over the hours 0:00 to23:59), because it covers the same time period as the residential air pollution estimates; however, Spearman correlations with other noise metrics including L_{night} and $L_{Aeq,16hr}$ were greater than 0.99. Individuals were assigned the modeled noise levels for their postcode (approximately 12 households per postcode). Less than 1% of postcodes were outside of the TRANEX model domain and could not be linked.

Rail and airport noise We identified individuals whose residential postcode was within the 50dB noise contours of over-ground railways and Heathrow airport. Noise contours came from strategic noise mapping under the first round of the Environmental Noise Directive. Data for over-ground railways were from Department for Environment, Food and Rural Affairs, supplied by Extrium Ltd. Aircraft noise from Heathrow airport was derived from annual average contours (2001) supplied by the Civil Aviation Authority.

Sociodemographic data Self-reported age, household income, and ethnicity were available from the LTDS. Ethnicity was collapsed into four ethnic groups: white (white – British, white – Irish, other white), Asian (Asian or Asian British – Bangladeshi, Asian or Asian British – Indian, Asian or Asian British - other Asian background, Asian or Asian British – Pakistani, Chinese), black (black or black British – African, black or black British – Caribbean, black or black British - other black background), and other (mixed - white and black Caribbean, mixed - other mixed background, mixed - white and black African, other ethnic group, mixed - white and Asian). For purposes of comparing exposure inequalities with household income, we used Lower Layer Super Output Area (on average 1500 people)-level deprivation data from the 2010 Index of Multiple Deprivation (IMD), a composite measure of area-level deprivation (**S-Figure 2**).(Communities and Local Governments, 2011) For better comparability with household income, we focused our analysis on the income domain of IMD, which is based on the proportion of households receiving income support. Area-level income deprivation was linked to individuals based on their residential postcode location. The distribution of participants' ethnicity by household income and area-level income deprivation is presented in **S-Figure3**.

Statistical Analysis All regression analyses took account of the hierarchical data structure: participants clustered within households (on average 2.2 participants per household). We explored bivariate relationships of continuous exposures with household income, ethnicity and area-level income deprivation with summary statistics and quantile regression. Quantile regression estimates conditional quantile functions, i.e. models in which the quantiles of the conditional distribution of the outcome are expressed as functions of the observed covariates. Quantile regression does not assume a distribution for the errors and is robust to extreme observations. More importantly, it is useful to describe complex relationships where the covariate effects are expected to be heterogeneous across the outcome distribution and thus associations based on the mean do not provide a complete picture. (Koenker, 2005) We used quantile regression because of the complex nature of the relationships we aimed to study and the highly skewed and heteroscedastic distributions for LHEM and TRANEX exposures. For example, estimates from the quantile regression at a given quantile of the distribution with household income as the single categorical covariate, represent the sample quantiles conditional on household income categories. We fit separate models for each exposure at 0.05 quantile intervals and used bootstrapping to estimate standard errors and confidence intervals, accounting for the hierarchical data structure. We tested for the presence of spatial autocorrelation in variograms of the residuals from the quantile regressions.

We explored whether exposure misclassification using ambient air pollution at residence rather than personal exposure differed according to age, socioeconomic and ethnic groups. We assumed that personal exposure estimates were a closer approximation to true personal exposure and fit models to the difference between residence and personal concentration. Models included the following covariates: age, age^2, ethnicity, household income, area-level income deprivation, and a random effect for household. We report exposure misclassification for variables with statistically significant associations with difference between residence and personal concentration.

To explore bivariate relationships for dichotomous exposures to rail and aircraft noise, we fit logistic models with separate models for household income, ethnicity, and area-level income deprivation using bootstrapping to estimate standard errors and confidence intervals. Statistical analysis were performed with R-3.3.2,(R Core Team, 2016) including packages: *tidyverse* (data manipulation), *ggplot2* (figures), *quantreg* (quantile regression), and lme4 (mixed models).(Koenker, 2016; Bates 2015; Wickham, 2016)

Results

The mean age of the study population was 37 years (sd 23). Distributions of residential and personal $PM_{2.5}$ and NO_2 as well as residential road traffic noise are presented in **Figure 1 and S-Table 2**. Personal exposure was generally lower than ambient residential exposure for both air pollutants, largely reflecting low penetration of outdoor air pollution indoors (Smith et al., 2016). **Table 1** presents mean air pollution, road-traffic noise, and percentage exposed to rail or aircraft noise according to household income, individual-level ethnicity, and area-level income deprivation (medians included in **S-Table 3**). Absolute and relative differences between the highest and lowest mean exposures to air pollution and road traffic noise according to household income were small and the correlations were weak (**Table 2**). Nonetheless, trends in air pollution exposure by household income were in different directions for residential and personal exposure. Trends in residential air pollution by household income were not monotonic; exposures generally decreased with increasing household income except for the highest income category (**Table 1**). Exposure gradients by area-level income deprivation were largest for NO_2, which is more spatially variable than $PM_{2.5}$. Participants living in the most deprived areas had the highest exposures for residential $PM_{2.5}$ and NO_2 as well as for personal NO_2, but not for personal $PM_{2.5}$ or road traffic noise. Similarly, increasing household income was only weakly correlated with lower residential air pollution, whereas increasing area-level deprivation was more strongly correlated with higher residential air pollution. (**Table 2**).

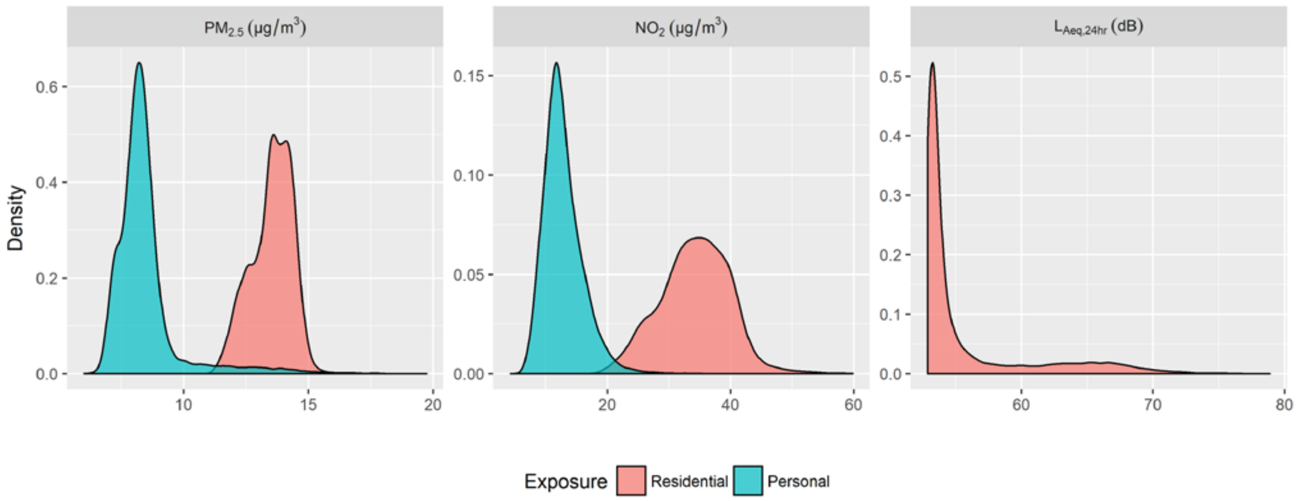


Figure 1. Probability density of residential and personal exposure to $PM_{2.5}$ and NO_2 and residential road traffic noise. Values greater than 20 μg/m^3 for $PM_{2.5}$ and 60 μg/m^3 for NO_2 (<0.1% of data) removed for purposes of visualization.

Table 1. Mean air pollution, road traffic noise, and percentage exposed to rail and aircraft noise by household income, ethnicity and area-level income deprivation

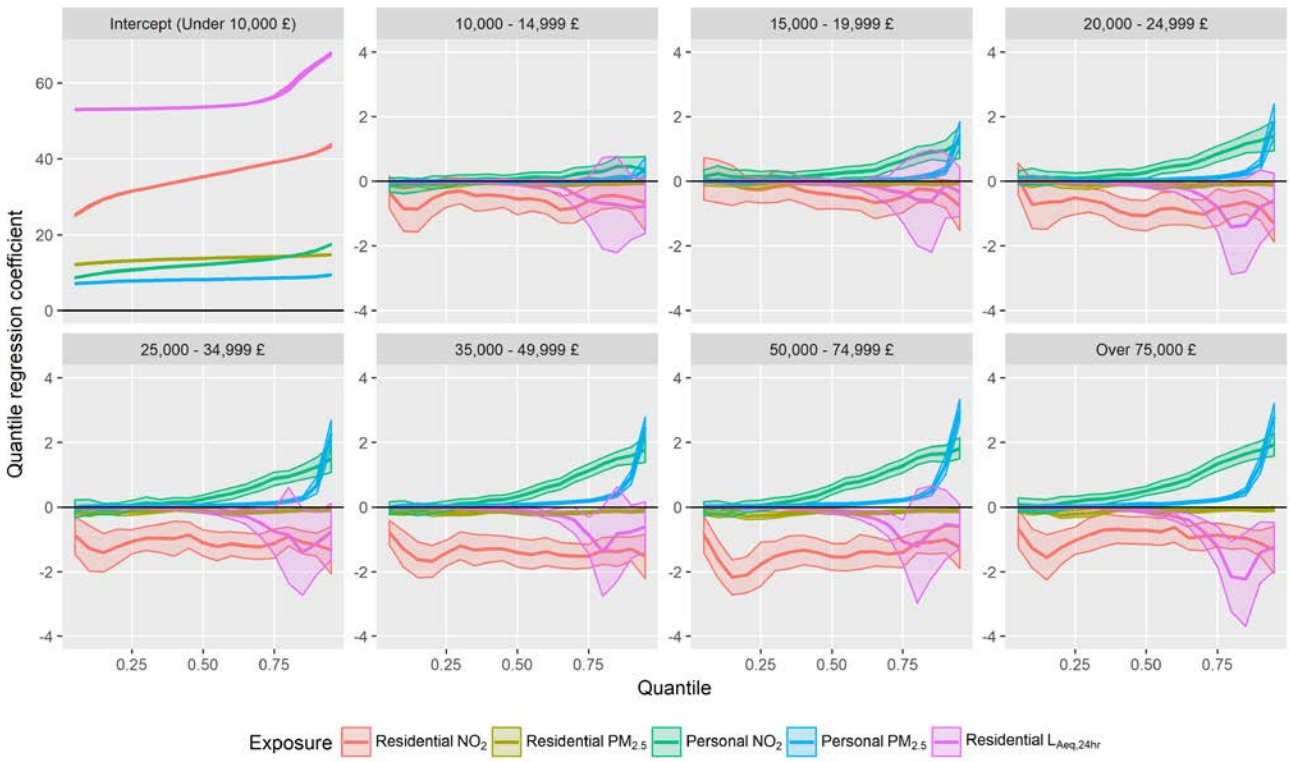
Means	N	Residential $PM_{2.5}$ (µg/m^3)	Personal $PM_{2.5}$ (µg/m^3)	Residential NO_2 (µg/m^3)	Personal NO_2 (µg/m^3)	Residential road traffic noise ($L_{Aeq,24hr}$ dB)	Rail noise (%)	Heathrow noise (%)
Income (£)								
Under 10000	8,327	13.63	8.29	35.13	12.48	56.11	12.7	11.4
10000 - 14999	4,762	13.55	8.33	34.61	12.57	55.87	12.9	11.6
15000 - 19999	4,318	13.56	8.44	34.79	12.89	55.96	12.4	13.2
20000 - 24999	3,883	13.54	8.50	34.37	13.01	55.79	12.0	10.7
25000 - 34999	5,760	13.50	8.53	34.02	12.92	55.79	14.3	12.3
35000 - 49999	6,464	13.48	8.59	33.79	13.07	55.81	12.3	13.2
50000 - 74999	5,573	13.46	8.64	33.67	13.18	55.80	11.3	13.3
Over 75000	5,992	13.51	8.62	34.18	13.22	55.57	11.4	16.7
Ethnicity								
White	29,479	13.49	8.47	33.90	12.81	55.75	12.0	13.8
Asian	7,592	13.61	8.60	34.87	13.05	56.15	12.7	10.5
Black	5,214	13.61	8.42	35.35	13.10	55.88	13.9	11.9
Other	2,516	13.70	8.50	35.69	13.16	56.08	13.4	10.5
Income deprivation quintiles								
1 (least deprived)	9,782	13.30	8.40	32.33	12.41	55.62	11.1	18.0
2	8,737	13.45	8.52	33.64	12.84	55.96	12.6	14.8
3	8,146	13.57	8.54	34.51	12.98	55.91	12.1	13.9
4	9,118	13.62	8.49	35.11	13.07	55.89	11.7	10.1
5 (most deprived)	8,128	13.73	8.49	36.12	13.19	55.83	14.5	7.0

Table 2. Spearman correlation coefficients between air pollution and road traffic noise exposures and household income and area-level income deprivation

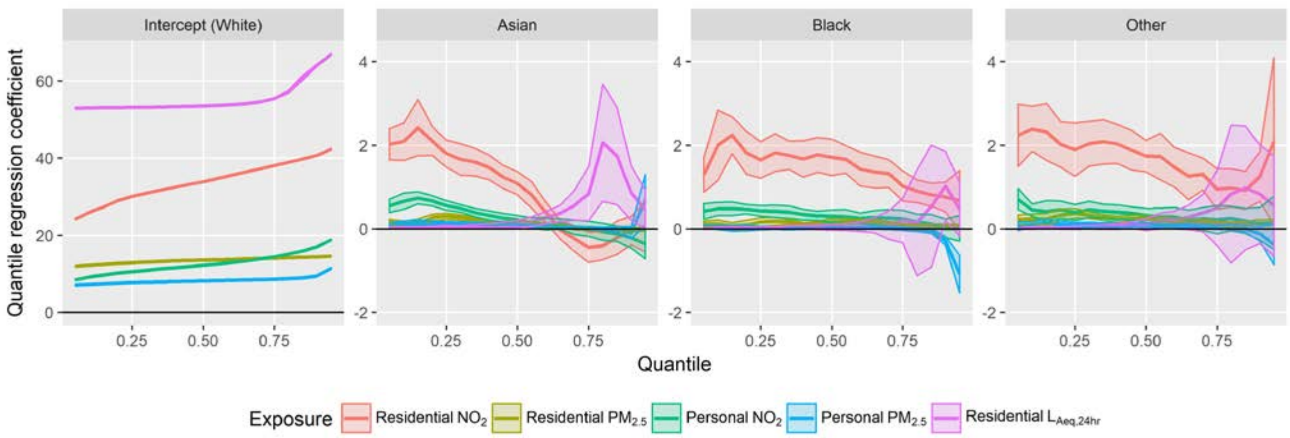
Spearman correlation	Residential $PM_{2.5}$ (µg/m^3)	Personal $PM_{2.5}$ (µg/m^3)	Residential NO_2 (µg/m^3)	Personal NO_2 (µg/m^3)	Residential $L_{Aeq,24hr}$ (dB)
Household income	-0.06	0.06	-0.07	0.07	-0.03
Income deprivation	0.19	0.08	0.25	0.11	0.07

Figure 2(a) presents the results of quantile regression exploring the relationship between air pollution and road traffic noise exposures with household income (models fit separately for each exposure)**.** The intercept represents the level of exposure at each quantile (e.g. 0.05 to 0.95) of exposure among participants with household income below £10,000. For example in this household income strata, exposure quantiles for residential NO_2 varied from 25.2 to 43.5 μg/m^3, while quantiles for personal $PM_{2.5}$ varied from 7.1 to 9.5 μg/m^3. For each quantile of exposure, residential NO_2 was approximately 1 μg/m^3 lower in the highest household income group relative to the lowest household income group (reference group, indicated as intercept), a difference that was statistically significant across all quantiles. Differences in residential $PM_{2.5}$ across income groups were small, consistent with the limited spatial variation in ambient $PM_{2.5}$ within the city. In contrast to residential NO_2, personal NO_2 was greater in higher income groups compared to the reference group at exposure quantiles 0.25 and above. Personal NO_2 was 1.9 (95% CI 1.6; 2.3) μg/m^3 higher in the 0.95 exposure quantile. In other words, the difference in exposure between the highest and lowest household income group did not depend on the level of exposure for residential NO_2, but for personal NO_2 the difference ranged between 0 and 1.9 μg/m^3 depending on the level of exposure. Personal $PM_{2.5}$ in the highest income group was indistinguishable from that in the lowest household income group until the 0.75 quantile, above which personal $PM_{2.5}$ was significantly higher in the highest household income group (2.8 (95%CI 2.4, 3.2) μg/m^3 difference in the 0.95 exposure quantile). Quantile regression results for each exposure adjusting for household income along with age and travel duration by mode are presented in **S-Figure 4**. Differences in personal exposure according to household income were largely explained by travel duration and mode.

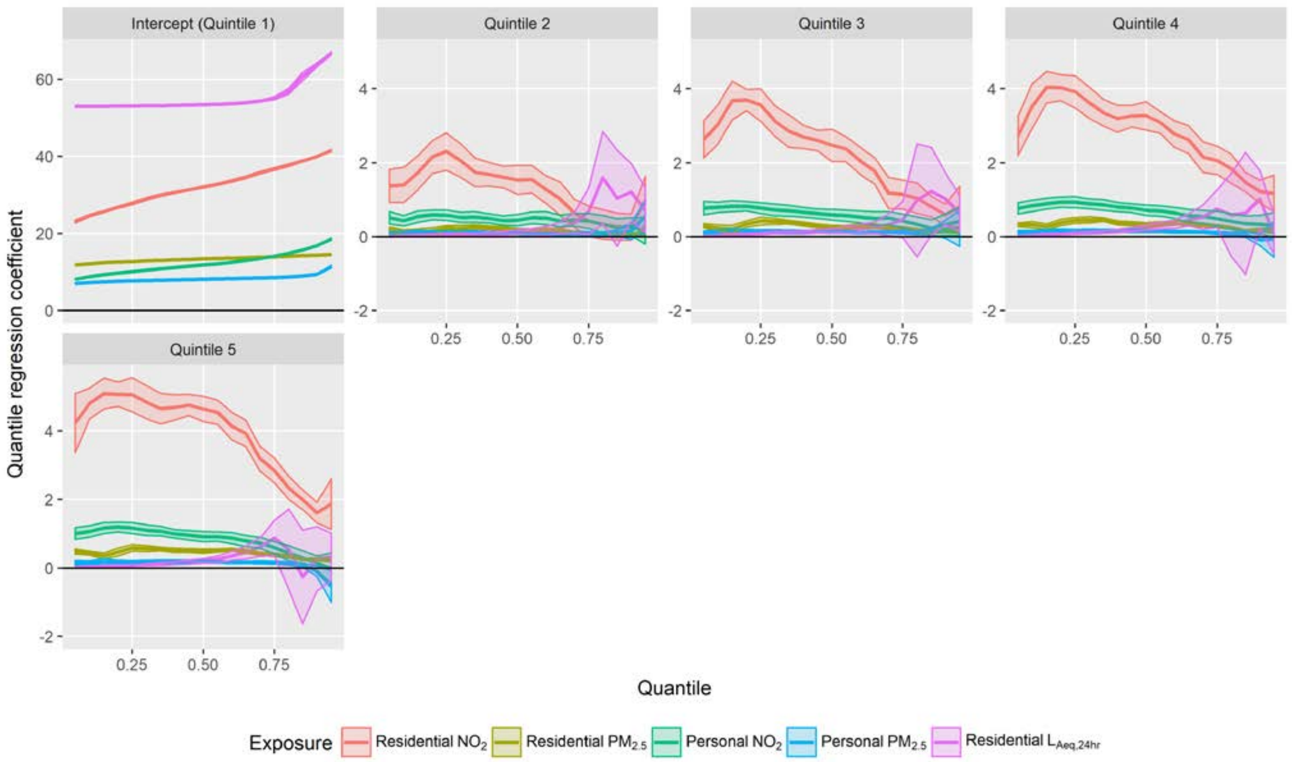
In the lowest household income strata, residential road traffic noise was approximately 53 dB until the 0.75 quantile, where it increased to nearly 70 dB in the 0.95 quantile. Differences in road traffic noise between the highest and lowest household income strata were negligible until the 0.75 exposure quantile. Above the 0.75 quantile, confidence intervals around the effect of household income on noise were wide, but the data suggest high household income was associated with lower noise exposure (e.g. -2.2 (95% CI -3.7,-0.8) dB at the 0.85 quantile).


Intercept (Under 10,000 £)
10,000 - 14,999 £
15,000 - 19,999 £
20,000 - 24,999 £
25,000 - 34,999 £
35,000 - 49,999 £
50,000 - 74,999 £
Over 75,000 £
Quantile regression coefficient
Quantile
Exposure
Residential NO_2
Residential $PM_{2.5}$
Personal NO_2
Personal $PM_{2.5}$
Residential $L_{Aeq,24hr}$

(a)


Intercept (White)
Asian
Black
Other
Quantile regression coefficient
Quantile
Exposure
Residential NO_2
Residential $PM_{2.5}$
Personal NO_2
Personal $PM_{2.5}$
Residential $L_{Aeq,24hr}$

(b)



(c)

Figure 2. Quantile regression coefficients (line) and 95% confidence intervals (shading) for residential and personal air pollution and residential road traffic noise according to (a) household income (b) ethnicity and (c) area-level income deprivation. Each exposure modelled separately.

The relationships between air pollution and road traffic noise exposures with ethnicity were complex **(Figure 2(b)**. Asians had higher residential NO_2 compare to whites below, but not above, the 0.6 quantile of exposure. Residential and personal exposures to $PM_{2.5}$ were similar for Asians and whites. Black and other ethnic groups had consistently higher residential NO_2 compared to whites. Maps of ambient NO_2 concentrations used to estimate residential exposure overlaid with participants' ethnicity at borough level show similar patterns **(S-Figure 5)**: while both Asian and whites were present in mid and high-range NO_2, participants other than whites were far less likely to live in locations with low NO_2. Asian ethnicity was associated with higher road traffic noise compared to whites above the 0.75 quantile of exposure.

The largest exposure differences according to quintiles of area-level income deprivation were for residential NO_2 (**Figure 2(c)**). However, differences were variable across the exposure range, with the largest differences at low residential NO_2 levels. In other words, low residential NO_2 consistently occurred in low income deprivation areas; however, high residential NO_2 occurred in both high and low income deprivation areas, for example in parts of Central London **(S-Figures 1 and 2)**.

Assuming estimated personal exposure to ambient pollution is a closer proxy for true personal exposure, we observed differences in the degree to which residential exposure overestimated personal exposure according to age, household income, and area-level income deprivation **(Figure 3)**. Differences according to ethnicity (adjusted for covariates) were small. The largest differences were seen for participants typically outside of the working age range (shown in figure for 10 and 70 year olds), whereas the lowest misclassification occurred for working age adults. The extent of overestimation by residential exposure generally increased with decreasing household income and increasing area-level income deprivation.

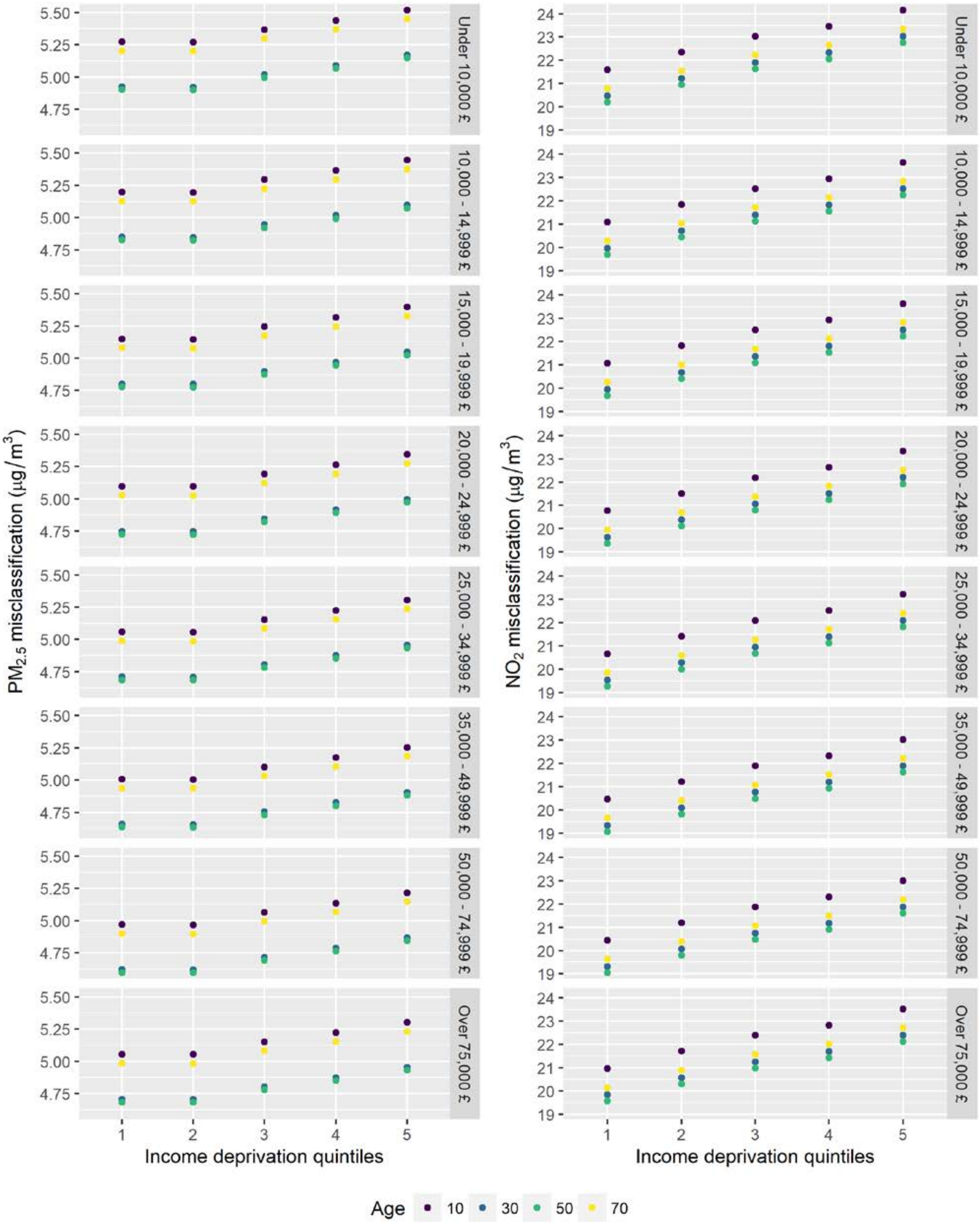
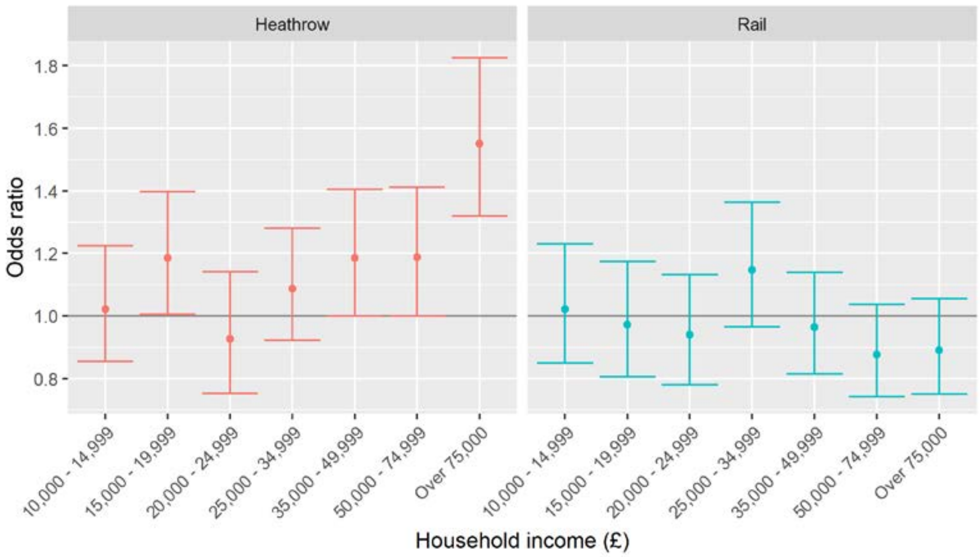
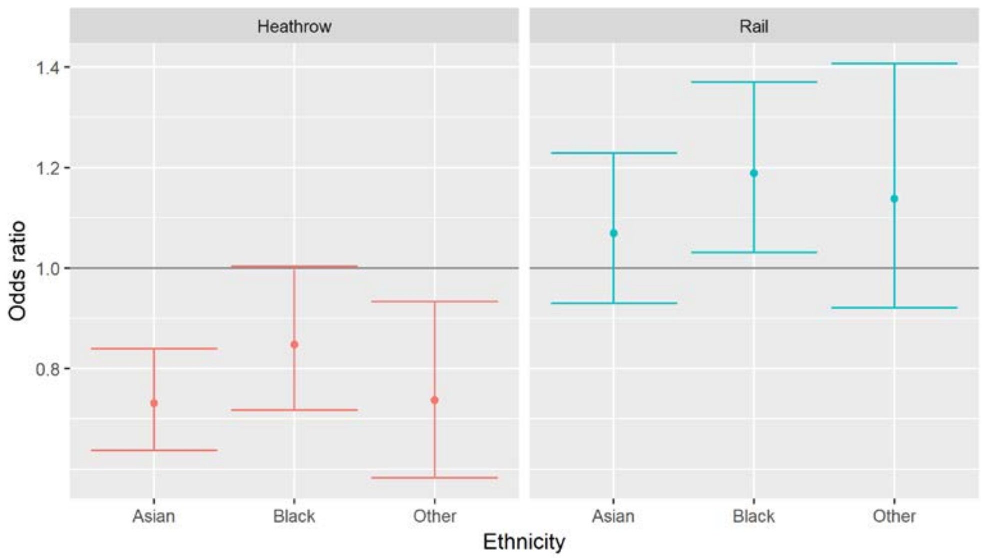


Figure 3. Exposure misclassification (µg/m^3) using residential compared to personal air pollution according to age (shown for select ages), household income, and area-level income deprivation. Estimates mutually adjusted and adjusted for ethnicity and household.

Individuals in the highest household income group had higher odds of living within a 50dB contour of aircraft noise from Heathrow airport (OR 1.55 (95% CI 1.32, 1.82)) compared to the lowest income group (**Figure 4a**). Individuals with Asian (OR 0.73 (95% CI 0.64, 0.84) and other ethnicity (OR 0.74 (95%CI 0.58, 0.93) had significantly lower odds of exposure to aircraft noise compared to whites (**Figure 4b).** For rail noise, no trend with household income was evident; however, the odds of living within a 50dB contour of rail noise was higher in black participants compared to whites (OR 1.19 (95%CI 1.03, 1.37)) (**Figure 4b**). The odds of exposure to aircraft noise steadily decreased with increasing area-level income deprivation (**Figure 4c)**). In contrast, the odds of exposure to rail noise were higher in the most deprived compared to least deprived quintile: OR 1.36 (95%CI 1.18, 1.58).



(a)



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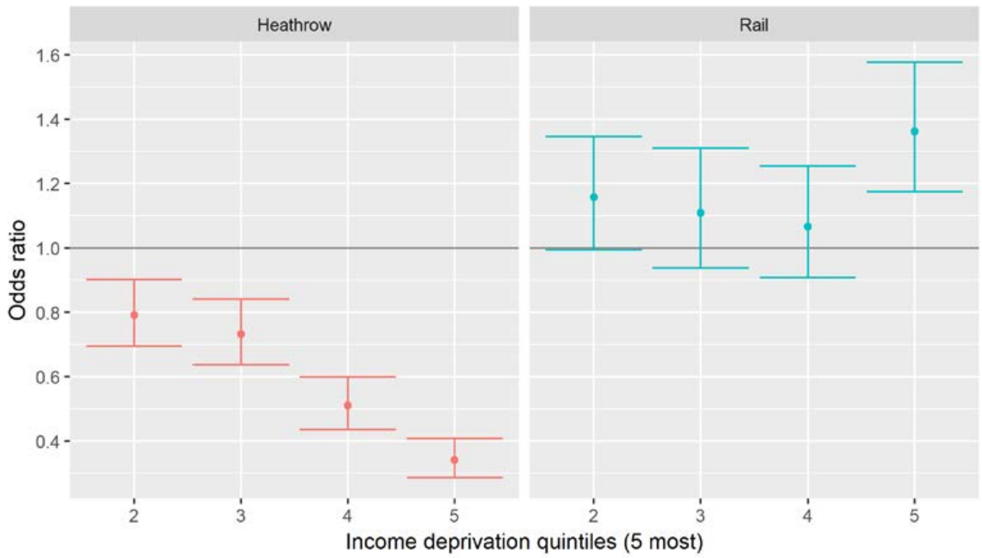

(c)

Figure 4. Exposure odds ratios (95% CI) to Heathrow airport and rail noise at residence according to (a) household income (reference: < 10,000 £) (b) ethnicity (reference: White) and (c) area-level income deprivation (reference: Quintile 1).

Discussion

Using a large dataset including individual-level data on household income and ethnicity, we observed a complex pattern of socioeconomic and ethnic inequalities in exposure to transport-related air and noise pollution in a large European city. In relation to our first objective, we observed inverse patterns in inequalities in air pollution when estimated at residence versus personal exposure. Compared to the lowest household income group, the highest household income group had consistently lower residential NO_2; however, most (from 0.25 quantile) participants in the highest household income group had higher personal NO_2 exposure. Air pollution exposure at residence consistently overestimated personal exposure with clear differences according to age, household income, and area-level income deprivation. These variables are often predictive of health status, which may lead to bias from differential exposure misclassification in epidemiological studies. In relation to our second objective, we observed socioeconomic and ethnic differences in the likelihood of exposure to aircraft and rail noise. Participants in the highest household income, white ethnicity, and lowest income deprivation groups were most likely to be exposed to aircraft noise from Heathrow airport, while participants in the group with the most area-level income deprivation were most likely to be exposed to rail noise. Socioeconomic and ethnic inequalities in road traffic noise were less pronounced.

We observed the highest personal air pollution exposure among participants with high household income, which was largely driven by differences in trip mode and duration by income level. Within the LTDS, increasing household income was associated with increasing number of trips per day and travel mode dominated by car, rail, and underground compared to bus and walking.(Transport for London, 2015) Car trips travelled the longest distances of all modes, and along with bus travel, had the longest travel times.(Transport for London, 2015) Similarly, the number of trips was highest for working age adults (25-59 years) and lowest for adults ≥65 years.(Transport for London, 2015) This is supported by our adjusted results (**S-Figure 4**), in which differences in personal exposure according to household income were minimal after adjusting for trip mode and duration.

Differences in $PM_{2.5}$ exposure on the scale of the socioeconomic inequalities observed here (up to 3 $\mu g/m^3$) have been associated with a range of adverse health outcomes in the London population, suggesting that the observed exposure inequalities could contribute to health inequalities. For example, a 1.1 $\mu g/m^3$ difference in $PM_{2.5}$ estimated using a similar model as the model used to generate the residential exposures in our study was associated with a decline in some measures of cognitive function in older adults.(Tonne et al., 2014) Similarly, a 2.2 μg/m^3 difference in $PM_{2.5}$ (from a similar exposure model) was associated with increased odds of low birth weight.(Smith et al., 2017) Long-term exposure to NO_2 has been linked to respiratory morbidity and mortality;(Health Canada, 2016; Faustini et al., 2014) although the expected health impacts from exposure differences on the scale observed in our study (up to 2 μg/m^3) are likely to be fairly small. A previous small-area study reported significant associations between aircraft noise from Heathrow and cardiovascular hospital admissions for exposures above 60dB compared to those below 50dB (Hansell et al., 2013); however, direct comparisons with our observed differences based on a binary exposure indicator are difficult.

Few previous studies of socioeconomic inequalities in air pollution exposure have focused on personal (modeled or measured) exposure. A recent study in London comparing measured air pollution in twelve typical commutes with origins with different area-level income deprivation and a single central London destination did not observe systematic differences in measured air pollution by deprivation.(Rivas et al., 2017) The highest particle exposures were observed for the commute originating in an area with high income deprivation; however, similar to our results (Table 1), the relationship between particle exposure and area-level income deprivation was not monotonic. Transport mode had a large impact on measured air pollution, with the highest levels of black carbon (BC) and PM of various size fractions (< 0.1 μm, 1 μm, 2.5 μm, 10 μm) measured during trips taken by underground and bus. Our results are broadly consistent with a modeling study based on a population in Flanders, Belgium that modeled personal exposure to BC according to household income.(Dons et al., 2014) The personal BC model took into account time-activity patterns, high spatial and temporal resolution ambient concentrations, in-traffic exposures during trips, and time spent indoors. BC exposure was higher at residence for individuals with lower household income, but higher household income individuals had more trips that were predominantly by car in traffic peak hours, and therefore had higher exposures while travelling.(Dons et al., 2014)

The direction of inequalities in noise exposures in our study was highly dependent on the sociodemographic indicator and noise source. There was an indication that road traffic noise was lowest among participants with highest household income and lowest area income deprivation, but confidence intervals were often wide. However, there was a clearer indication that Asian participants had higher road traffic noise exposures compared to whites, likely because they live closer to high traffic roads. On the other hand, white individuals, those with high household income, and living in low income deprivation areas were more likely to be exposed to aircraft noise from Heathrow, while individuals in high income deprivation areas were more likely exposure to rail noise.

Other studies have similarly found sensitivity in the direction and magnitude of inequalities to noise according to indicator of socioeconomic position and noise source. A survey of German adults (n=7100) found higher frequency of self-reported road traffic and neighborhood noise annoyance among individuals with lower disposable income, although, associations were sensitive to specific indicators of social status.(Laußmann et al., 2013) Only a weak association was observed between income and aircraft noise. A non-linear association between census block level deprivation index and road traffic noise was associated with the highest exposures in an intermediate deprivation group in Marseille, France.(Bocquier et al., 2013) In Montreal, Canada, environmental noise (largely from transportation and industry) was correlated (Pearson) with area-level deprivation for a range of deprivation metrics.(Dale et al., 2015) In contrast, a study of road traffic noise in the city of Paris observed people living in socially advantaged neighborhoods in terms of education, dwelling value, and country of citizenship were exposed to higher noise compared to more deprived counterparts.(Havard et al., 2011) Results showed sensitivity to the definition of non-French citizenship: more refined analyses taking into account the level of development of the country of citizenship showed higher noise levels among people living in neighborhoods with a higher proportion of citizens from advantaged countries.(Havard et al., 2011)

Socioeconomic inequalities in air pollution have been found to be sensitive to analytical methods and the use of individual versus area-level socioeconomic data.(Hajat et al., 2015) Our analysis also highlights other factors to which results are sensitive. We observed different results when considering inequalities based on residential versus personal air pollution exposure. We also observed that socioeconomic and ethnic inequalities are often not uniform across the exposure distribution. Our analysis shows the value of quantile regression, frequently used in economic analyses of inequality but, to our knowledge, not previously applied to inequalities in environmental exposures.(Martins and Pereira, 2004) Analyses based on traditional regression methods modeling only the mean would not have captured the full extent of exposure inequalities in our data. Our data indicate inequalities in personal air pollution according to household income at high, but not low exposures. Similarly, differences in residential NO_2 according to area-level income deprivation are greatest at the lowest exposures, but disappear at the highest exposures. This pattern is consistent with our previous research in London, indicating different correlations between air pollution and area-level income deprivation across the air pollution exposure range: correlations between exhaust-related primary $PM_{2.5}$ and deprivation were 0.16, 0.24, 0.12 and −0.17 according to increasing exposure category. (Halonen et al., 2016)

While using personal rather than outdoor residential air pollution is attractive due to reduced exposure misclassification, there may be a trade-off with more potential for residual confounding in epidemiological studies.(Weisskopf and Webster, 2017) Our data are consistent with the causal model proposed by Weisskopf and Webster (**S-Figure 6**), which identifies the potential for confounding by factors associated with both residential and personal air pollution. Residential air pollution was associated with area-level deprivation; however, the extent of confounding by area-level deprivation will also depend on the strength of association between deprivation and health, conditional on other covariates. Personal exposure was influenced by personal behaviors in our data, namely travel mode and duration, as well as age. Participants with active travel modes had lower personal exposure,(Smith et al., 2016) and active travel has been associated with a number of health benefits,(Celis-Morales et al., 2017) indicating that travel mode could be an important confounder of associations based on personal exposure. Our data do not suggest that household income would be a strong confounder of associations between personal $PM_{2.5}$ and health outcomes, although confounding is somewhat more likely with personal NO_2. Although the quantile regression results indicate stronger associations between household income and personal exposure at high exposures, epidemiological estimates are typically based on mean exposure and would be less affected. For example, mean personal $PM_{2.5}$ corresponds roughly with the 70^{th} percentile of the exposure distribution (60^{th} percentile for personal NO_2) where differences according to household income are small (**Figure 2**), particularly after adjusting for other covariates (**S-Figure 4**).

The main strengths of our analysis are the large dataset including information on household income, individual-level ethnicity, and travel behavior from a representative sample of the London population. These data are combined with estimates of personal exposure, which take into account travel behavior and penetration of outdoor air pollution indoors at locations between trips. In addition, we used data on residential noise exposure to multiple transport sources, contributing to the currently small literature on noise inequalities. Our analysis uses quantile regression, which is well suited for, but not widely used in research of environmental inequalities.

A limitation of our analysis is that the residential, personal air pollution and road traffic noise data were based on models rather than direct measurements. While models allowed us to estimate exposures for a large sample, comparisons between residential and personal air pollution may be affected by differences in the models' performance. Sensitivity of the model of personal exposure has been evaluated by Smith and colleagues: model estimates were most sensitive to the parameterization of penetration of outdoor air indoors.(Smith et al., 2016) Notably, the model did not account for occupational exposures or indoor sources, which may be higher for individuals with lower socioeconomic position.(Jantunen et al., 2000) Evaluation of the model for road traffic noise against measurements is reported by Gulliver and colleagues.(Gulliver et al., 2015) The relatively small inequalities in road traffic noise we observed are within the range of model error and should be interpreted with caution. We did not account for spatial autocorrelation in residential air pollution (no autocorrelation was present for other exposures), which may have led to artificially small standard errors in the regression estimates. We explored methods that take into account the spatial structure of the data in the context of quantile regression (e.g. adjusting for spatial units with fixed or random effects, or spatial smooth effects). While these methods addressed the spatial autocorrelation, they explained much of the variability of the response variable and shrunk the inequality effects, which are also clustered in space. We therefore report non-spatially adjusted results given that our focus was not on hypothesis testing. Also, we combined data from a number of sources, resulting in some temporal mismatch in the data (**S-Table 1**). This is most relevant for the aircraft noise from Heathrow airport, which was from year 2001. The inequalities observed with respect to Heathrow airport, a single source, are likely specific to the particular geography of London. However, we observed complex patterns in inequalities that varied by air pollution exposure estimation method and noise transport source; the presence of complexity and need for analytical methods to more fully characterize this complexity is likely to be widely generalizable across cities.

In conclusion, all transport sources were associated with some form of exposure inequalities, although the patterns were complex and the direction of inequalities was not consistent across exposure metrics. Analysis based on individual-level socioeconomic data and personal exposure provide a more accurate picture of which groups of individuals are most exposed, which can be notably different than the picture based on more aggregated data. Finally, quantile regression, a common tool in economic analysis of inequalities, is a useful approach for more fully characterizing environmental exposure inequalities across the full range of exposures. Socioeconomic and ethnic inequalities in integrated measures of multiple environmental stressors warrant further investigation.

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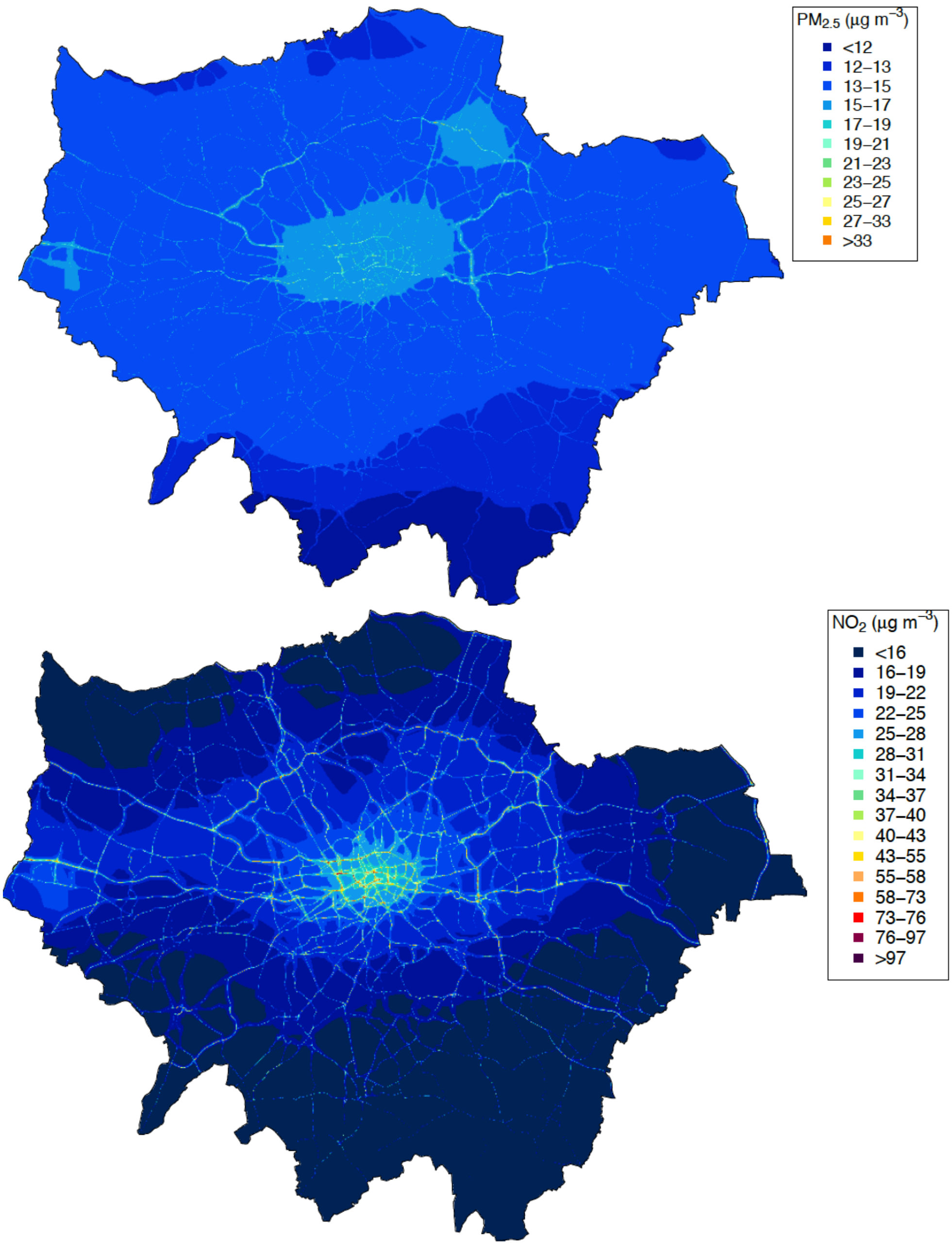
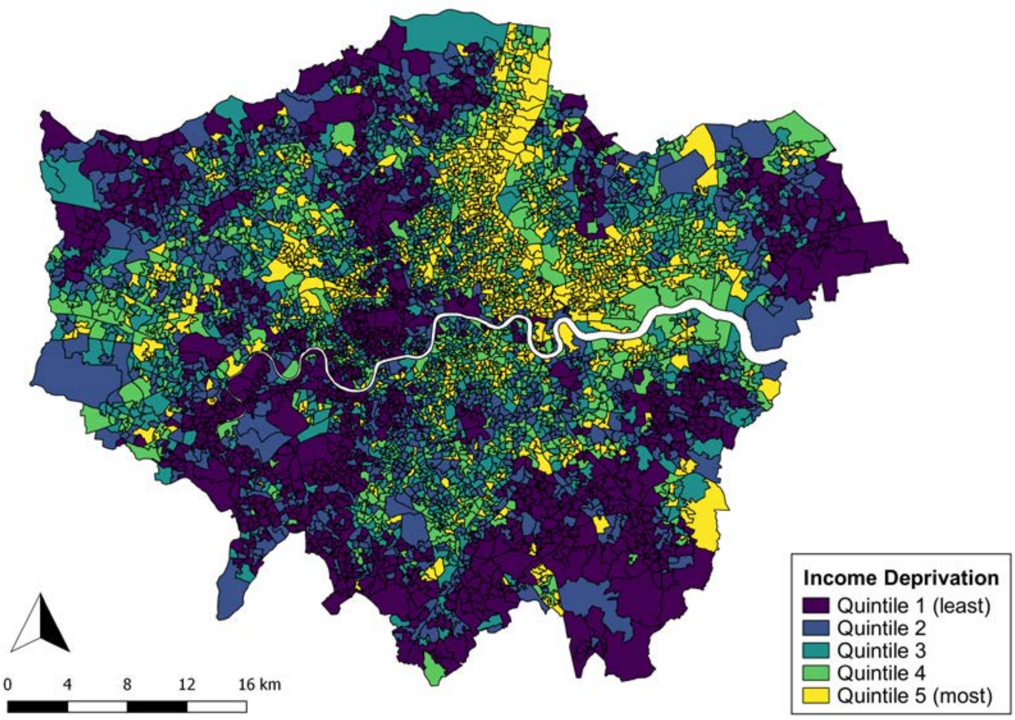
Supplementary information

S-Table 1. Summary of spatial resolution and time period covered by data sources

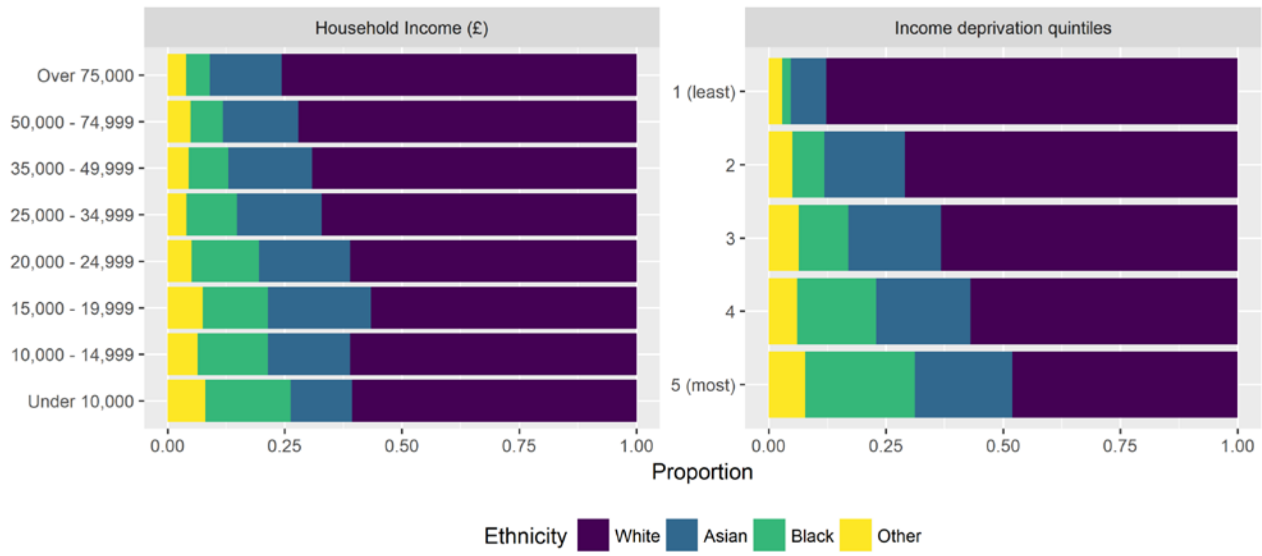
Data	Source/Model	Resolution	Date
Age, sex, trips, travel model, trip duration, household income, ethnicity	London Travel Demand Survey from Transport for London; https://tfl.gov.uk/corporate/publications-and-reports/london-travel-demand-survey	Residential postcode centroid (in England on average 12 households per postcode)	2006-2010
Personal $PM_{2.5}$, NO_2 exposure	London Hybrid Exposure Model (Smith et al., 2016)	Residential postcode centroid	Annual average 2011
Outdoor $PM_{2.5}$, NO_2 exposure	CMAQ-Urban (Beevers et al., 2012)	20m x 20m surface linked to residential postcode centroid	2011
Road traffic noise	TRAffic Noise EXposure model (TRANEX) (Gulliver et al., 2015)	Residential postcode centroid	Annual average 2003-2010
Rail noise (binary indicator of location within 50dB L_{DAY} noise contour)	UK Department for Environment, Food and Rural Affairs; Environmental Noise Directive – Noise Mapping	Residential postcode centroid	Annual average 2006
Aircraft noise from Heathrow airport (binary indicator of location within 50dB L_{DAY} noise contour)	Civil Aviation Authoritiy; UK civil aircraft noise contour model (ANCON)	Residential postcode centroid	Annual average 2001
Neighbourhood-level income deprivation	2010 Index of Multiple Deprivation – Income Domain(ref)	Lower Layer Super Output Areas (LSOAs): on average 1500 residents	2008



S-Figure 1. $PM_{2.5}$ and NO_2 concentrations (interpolated from 20x20m grid) used to estimated residential exposures



S-Figure 2. Quintiles (based on sample) of Lower Layer Super Output Area level income deprivation (2010)



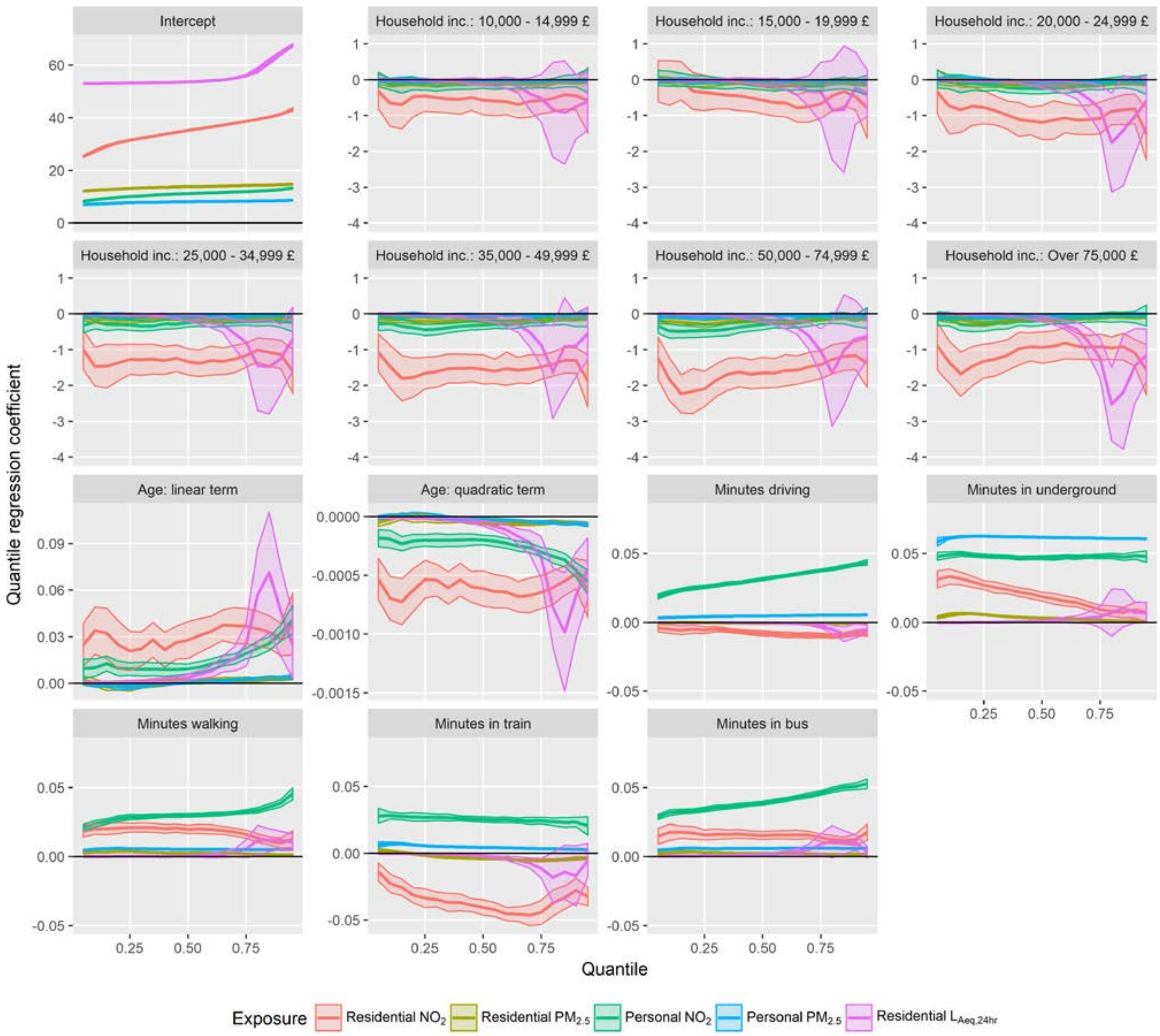
S-Figure 3. Proportion of ethnicity of participants according to household income and area-level income deprivation

S-Table 2. Summary statistics for air pollution exposures and road traffic noise

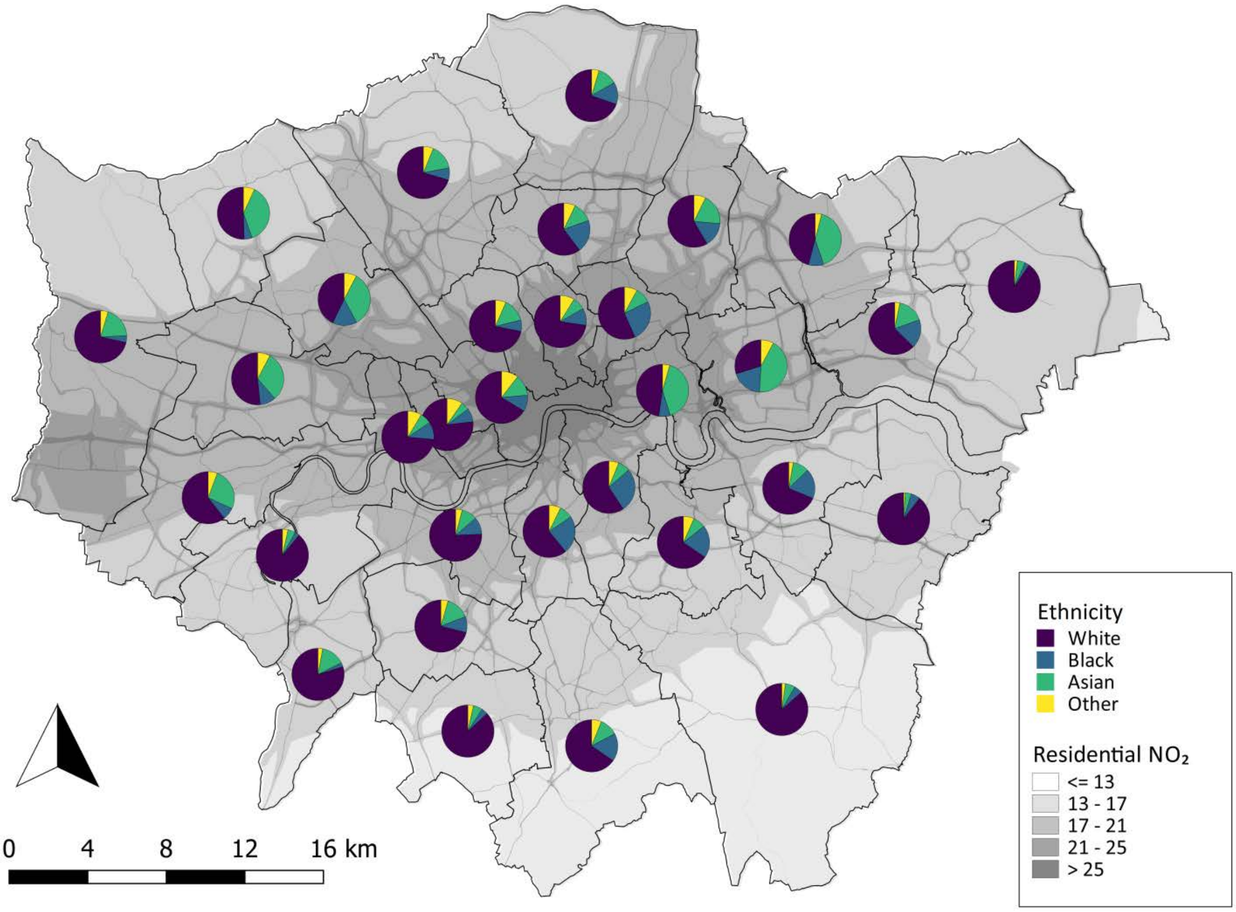
Model	n	mean	sd	min	Q1	median	Q3	max
Residential $PM_{2.5}$	45,079	13.5	0.8	11.2	13.0	13.6	14.2	20.0
Personal $PM_{2.5}$	45,079	8.5	1.4	6.0	7.8	8.2	8.7	32.2
Residential NO_2	45,079	34.3	5.8	17.8	30.7	34.5	38.3	88.1
Personal NO_2	45,079	12.9	3.3	4.3	10.8	12.3	14.5	55.3
Noise $L_{Aeq,24hr}$	44,974	55.9	4.7	52.9	53.2	53.6	55.6	78.9

S-Table 3. Median air and noise pollution by household income, ethnicity and area-level income deprivation

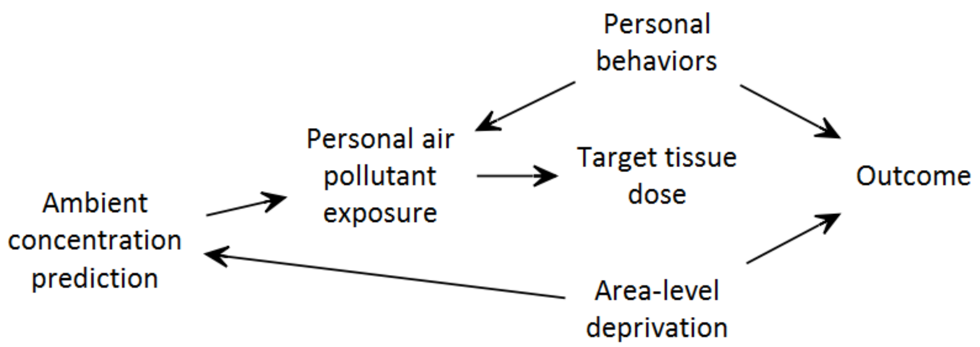
Medians	N	Residential $PM_{2.5}$ (µg/m^3)	Personal $PM_{2.5}$ (µg/m^3)	Residential NO_2 (µg/m^3)	Personal NO_2 (µg/m^3)	Residential road traffic noise ($L_{Aeq,24hr}$ dB)
Income (£)						
Under 10000	8,327	13.73	8.18	35.30	12.10	53.63
10000 - 14999	4,762	13.66	8.20	34.77	12.18	53.58
15000 - 19999	4,318	13.67	8.21	34.91	12.32	53.58
20000 - 24999	3,883	13.59	8.22	34.24	12.37	53.51
25000 - 34999	5,760	13.59	8.23	34.19	12.34	53.53
35000 - 49999	6,464	13.56	8.25	33.89	12.42	53.55
50000 - 74999	5,573	13.56	8.26	33.76	12.64	53.51
Over 75000	5,992	13.61	8.27	34.58	12.60	53.50
Ethnicity						
White	29,479	13.56	8.20	33.91	12.24	53.52
Asian	7,592	13.72	8.29	35.00	12.46	53.64
Black	5,214	13.73	8.22	35.62	12.54	53.56
Other	2,516	13.82	8.29	35.66	12.56	53.62
Income deprivation quintiles						
1 (least deprived)	9,782	13.40	8.12	32.00	11.78	53.41
2	8,737	13.56	8.20	33.53	12.22	53.53
3	8,146	13.64	8.24	34.47	12.37	53.56
4	9,118	13.71	8.27	35.27	12.49	53.65
5 (most deprived)	8,128	13.89	8.30	36.63	12.69	53.61



S-Figure 4. Quantile regression coefficients and 95% confidence intervals for residential and personal air pollution and residential road traffic noise according to household income. Each exposure fit separately to a model including household income, travel duration by mode, and age simultaneously.



S-Figure 5. Residential NO_2 concentrations overlaid with ethnicity of participants within each borough



S-Figure 6. Causal diagram illustrating confounding of ambient and personal exposure to air pollution in relation to a health outcome (adapted from Weisskopf and Webster)(Weisskopf and Webster, 2017)**.**