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# The association between $PM_{2.5}$, greenness (NDVI) and road noise exposures and the academic performance of state school pupils in England: a National Pupil Database study☆

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ABSTRACT

Research suggests that exposure to air pollution, greenspace and noise may affect children's academic performance, however further large-scale, longitudinal evidence is needed. This study quantifies the relationship between $PM_{2.5}$ and children's academic performance while considering the effects of greenness and road noise using the National Pupil Database. 1,048,167 children starting state school in England at ages 4–5 years in 2005 and 2006 were followed for 12 years. Annual average environmental exposures at home and school were measured since the start of formal education up until each academic assessment. The associations of $PM_{2.5}$ with cohort-standardised Z-scores of academic performance at ages 4–5, 6–7, 10–11 and 15–16 years were investigated using multilevel mixed effects linear regression models controlling for greenness, road noise and other individual, school and areal characteristics. $PM_{2.5}$ was related to −0.055 (95 % CI: 0.064, −0.045) lower Z-scores per inter-quartile range (IQR, 2.08 μg/m$^3$) exposure increase at ages 15–16 years, but not at other ages. Greenness was associated with 0.016 (95 % CI: 0.009, 0.022), 0.016 (95 % CI: 0.009, 0.024) and 0.035 (95 % CI: 0.029, 0.04) higher Z-scores at ages 6–7, 10–11 and 15–16 years, respectively, per IQR (0.1 NDVI) exposure increase. Road noise was related to −0.014 (95 % CI: 0.018, −0.01), −0.006 (95 % CI: 0.01, −0.003), −0.009 (95 % CI: 0.014, −0.005) and −0.008 (95 % CI: 0.012, −0.004) lower Z-scores at ages 4–5, 6–7, 10–11 and 15–16 years, respectively, per IQR (ages 4–5, 7.06 dB; 6–7, 6.81; 10–11, 6.56; 15–16, 6.32) exposure increase. This nation-wide study suggests that greater exposure to $PM_{2.5}$ and road noise are harmful to academic performance later in school and throughout school, respectively, while greenness exposure has beneficial impacts across most school age groups in this sample. Reducing $PM_{2.5}$ and road noise and increasing greenness around children's homes and schools may improve academic performance.

## 1. Introduction

Emerging evidence suggests that interrelated characteristics of the physical environment, namely $PM_{2.5}$, greenness and road noise, may impact children's cognitive development (Milojevic et al., 2021; Dadvand et al., 2015; Foraster et al., 2022). $PM_{2.5}$ refers to fine particulate matter with a diameter less than or equal to 2.5 μm, often produced through combustion, that contributes to ambient air pollution levels globally (Zawar-Reza and Spronken-Smith, 2005). Greenness indicates the degree of living vegetation in an area (Vilcins et al., 2022), and has the potential to reduce levels of harmful pollutants, such as $PM_{2.5}$ and road noise (Hartig et al., 2014). Road noise is emitted from human activities around roads, such as motorised transport, which is also a common source of $PM_{2.5}$ (Adza et al., 2023).

Environmental factors may affect children's cognition through direct entry into the body in the case of $PM_{2.5}$ (Thangavel et al., 2022), disruption of mental and physical processes through road noise exposure (Thompson et al., 2022), and direct and indirect promotion of healthy development from greenness exposure (Hankey and Marshall, 2017). Children's cognitive level is influenced by a myriad of biological, social and environmental factors (del Carmen Ruiz et al., 2016), and can be measured in numerous ways, including through proxy indicators, such

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as academic performance at school (Requia and Adams, 2022; Minaravesh and Aydin, 2023). Few studies have examined the effects of multiple environmental exposures on children's cognitive development (Thompson et al., 2024; Saenen et al., 2023).

Research demonstrates some detrimental effects of $PM_{2.5}$ on children's working memory and intelligence quotient (IQ) among multiple studies in Spain (Lertxundi et al., 2019; Alvarez-Pedrerol et al., 2017; Rivas et al., 2019), China (Gui et al., 2020), and the United States (US) (Chiu et al., 2016; Wang et al., 2017; Harris et al., 2015). Other longitudinal studies in the US and Brazil indicate long-term $PM_{2.5}$ may also be related to lower primary and secondary school performance (Mullen et al., 2020; Requia et al., 2022). On the other hand, cross-sectional evidence from Wales found no measurable associations with final year exams (Mizen et al., 2020), highlighting possible age-dependent and exposure timing air pollution sensitivities (Gartland et al., 2022; Castagna et al., 2022). Evidence implicates oxidative stress, neuroinflammation, and changes to the brain's cortex and grey matter as possible pathways of effect from $PM_{2.5}$ to cognition (Thangavel et al., 2022; Costa et al., 2020; Cserbik et al., 2020; Guxens et al., 2018).

Compared to $PM_{2.5}$, more studies focus on greenness in relation to academic performance. Research using the Normalised Difference Vegetation Index (NDVI) presents some positive (Requia and Adams, 2022; Wing et al., 2019) and null (Markevych et al., 2019) associations between greenness and academic performance across school ages in the US, Brazil and Germany. Other measures akin to greenness, such as exposure to tree (Kweon et al., 2017; Li et al., 2019; Tallis et al., 2018) or vegetation cover (Ahmed et al., 2022), also support a beneficial long-term effect on performance at school; however, socioeconomic factors (Sivarajah et al., 2018; Beere and Kingham, 2017) and population density (Browning and Locke, 2020) may confound this association. Generally, diverse greenness metrics and causal pathways pose methodological complexities (del Carmen Ruiz et al., 2016). Mechanistic studies suggest that greenness may improve academic performance by reducing harmful exposures and encouraging physical activity, attention restoration and social cohesion (de Keijzer et al., 2016).

An emerging research area examines ambient noise and academic performance. Evidence suggests that noise exposure in and around schools and homes may have detrimental impacts on primary school pupil performance in France and the United Kingdom (UK) (Pujol et al., 2013, Shield and Dockrell, 2008). Aircraft noise may also have a negative relationship with primary school children's reading performance (Klatte et al., 2016; Clark et al., 2006), but socio-economic factors (Clark et al., 2006), and native language (Papanikolaou et al., 2015) may confound this association. Evidence for road noise exposure is mixed, sample sizes remain modest, and heterogenous age groups, outcomes and exposure methods, including location and length of exposure, challenge comparison between studies (Papanikolaou et al., 2015; Xie et al., 2011; Matheson et al., 2010; Foraster et al., 2022). Noise exposure may lead to poorer academic performance by disrupting sleep and attention, and increasing stress, learned helplessness (Thompson et al., 2022), oxidative stress and neuroinflammation (Hahad et al., 2022).

Given accumulating evidence of the environmental-cognitive link, some studies take multi-exposure approaches. Multi-exposure evidence focusing on a range of outcomes shows positive associations with tree cover and greenness (van Wel et al., 2021; Donovan et al., 2018; Saenen et al., 2023), and negative relationships with $PM_{2.5}$, $NO_2$, road and aircraft noise (Julvez et al., 2021; van Kempen et al., 2012; Thompson et al., 2024). However, results also demonstrate null or unexpected directions of effects (van Wel et al., 2021), inconsistent findings across home and school exposures, and attenuated results with mutual adjustment. Further research explores greenness impacts mediated by $PM_{2.5}$ or road noise (Jarvis et al., 2021; Asta et al., 2021; Binter et al., 2022). However, as different types of greenspaces may relate distinctly to air and noise pollutants (Carver et al., 2022; Claesen et al., 2021) most multi-exposure studies take a mutual adjustment approach (Buczylowska et al., 2023; Bloemsma et al., 2022).

There is increased attention on the economic, social and health consequences of air pollution, greenspace, and noise among vulnerable groups in the UK (Public Health England, 2020; Marmot et al., 2020). Although research provides moderate evidence of associations between environmental exposures and children's cognition and academic performance, heterogeneity in exposure and outcome measures challenge consistency (Milojevic et al., 2021). In addition, longitudinal, nation-wide studies that utilise public data on multiple exposures, consider a comprehensive set of covariates, and include outcome measurements throughout development are lacking (Lopuszanska and Samardakiewicz, 2020).

This study examines the associations between long-term residential and school $PM_{2.5}$, greenness and road noise exposures and the academic performance of children in state schools in England from 2005 to 2018 while accounting for related individual, school and areal characteristics using the National Pupil Database (NPD). The authors used parallel methodology in another national dataset, the Millennium Cohort Study, that did not detect any effects (Garkov et al., 2024a). This research aims to further explore $PM_{2.5}$, greenness and road noise exposure in relation to academic performance using a larger scale study to advance understanding of the relationships and inform future research.

## 2. Methods

### 2.1. Study population

The national curriculum in England from ages 4–5 to 15–16 years is organised into blocks referred to as 'Key Stages' (KS), with pupils' academic performance formally assessed at the end of each KS. This study utilises the National Pupil Database (NPD), an administrative dataset of all pupils in state schools in England, and school-level annual school census (SLASC) data from the Department for Education (DfE) (Jay et al., 2019). The NPD annually records pupil-level exam performance, census data, residential addresses at postcode level (on average fifteen properties per postcode) and schools' unique reference numbers (URNs).

This study targets over one million children ($n$ = 1,048,167) who began their first year of primary school, known as the Reception year, in state schools in September of 2005 (first cohort) or 2006 (second cohort), and completed the last national curriculum block, Key Stage 4 (KS4), in May of 2017 (first cohort) or 2018 (second cohort). Residential postcodes were verified with the Office for National Statistics (ONS) Postcode Directory (May 2021) with more than one usual resident at the time of the 2011 Census (Office For National Statistics, 2021). The school URNs and their postcodes from 2005 to 2018 were confirmed with the DfE's register of schools in England, Get Information About Schools (GIAS), to reflect their systematic change (Department For Education, 2023a). An individual profile of environmental exposures detailed below, and other factors known to impact academic performance were created for each pupil at home and school postcodes annually over the 12-year follow-up period. Only pupils with complete information on residential and school exposures, academic performance and pre-defined covariates at each KS were included. This resulted in analytic samples comprised of 553,282 children at Early Years Foundation Stage Profile (EYFSP), 979,978 children at Key Stage 1 (KS1), 745,123 children at Key Stage 2 (KS2) and 708,273 at KS4.

### 2.2. Academic outcomes

Children's academic performance was measured through formal assessments at school in May at the end of each KS at ages 4–5 years at EYFSP, ages 6–7 years at KS1, ages 10–11 years at KS2 and ages 15–16 years at KS4. These assessments are uniform across England and are part of the national curriculum. For children starting Reception in 2005 (first cohort), academic performance at EYFSP was recorded only for a 10 % random sample of pupils, whereas performance at the remaining KSs were recorded for all pupils. For children starting Reception in 2006 (second cohort), all academic performance data was recorded across all KSs. For EYFSP, the teacher-assessed standardised total score in Early Learning Goals is used, which determines whether each child has the emerging or expected level across six areas of learning related to personal, social and emotional development; communication, language and literacy; problem-solving, reasoning and numeracy; knowledge and understanding of the world; physical development; and creative development (Department For Children Schools And Families, 2008). Standardised total scores at KS1 and KS2 were created by taking an average of the standardised English and mathematics point scores at KS1 and KS2, respectively. At KS4, the standardised attainment 8 score is employed, representing the average measure of each pupil's progress across their eight best performing subjects taken at the General Certificate of Secondary Education (GCSE) level (Department For Education, 2023c). All measures of academic performance across KSs were standardised by creating Z-scores from the mean and standard deviation of the scores from the first cohort and second cohort, respectively.

### 2.3. Exposure assessments

#### 2.3.1. Fine particles ($PM_{2.5}$)

Maps of annual average $PM_{2.5}$ levels across England from 2005 to 2018, measured in micrograms per cubic metre (μg/m$^3$) at 1 × 1 kilometre (km) resolution, were obtained from the Department for Environment, Food & Rural Affairs (Defra) modelled background pollution data (Department For Environment Food & Rural Affairs, 2020). Background $PM_{2.5}$ concentrations are calculated by summing contributions from various point and areal emission sources described in the National Atmospheric Emissions Inventory (NAEI) in industrial, domestic, road traffic, rural areas, amongst others. Further contributions to background $PM_{2.5}$ concentrations, such as secondary (in)organic aerosols, regional primary particles, regional calcium and iron rich dusts from re-suspension, iron-rich dusts from re-suspension due to vehicle activity, sea salt and residuals, are also included. In addition, the roadside increment concentrations are calculated for urban major road census points (A-roads and motorways). This provides robust roadside assessments while retaining the link with Automatic Urban and Rural Network (AURN) measurement data to calibrate this component of the model. Further detailed modelling methodology is described elsewhere (Ricardo Energy & Environment, 2021). To represent annual exposure to $PM_{2.5}$ at home and school, the estimated closest value on the 1 km $PM_{2.5}$ grid to the centroid of residential and school full-postcode boundaries each year (2005–2018) were determined in Quantum Geographic Information System (QGIS), version 3.16.8 'Hannover'.

#### 2.3.2. Greenness

Greenness was measured by the Normalised Difference Vegetation Index (NDVI) products, a remote sensing technique used to quantify the health and density of vegetation, generated by Copernicus Global Land Service, the Earth Observation programme of the European Commission (Copernicus Global Land Service, 2019). The NDVI is calculated using the Red and Nir reflectance values using the 10-daily Top of the Canopy reflectance, measured by the PROBA-VEGETATION sensor at 1 km resolution (copyright BELSPO and distribution by VITO NV) (Toté et al., 2020). NDVI values range from −0.08, indicating burnt areas, to 0.92, indicating the greenest areas; any values outside of this range indicate the presence of water or missing values where data was not collected. The nearest annual average NDVI values from the centroid of residential and school full-postcode boundaries on the 1 × 1km grid were allocated using QGIS across the 12-year follow-up period from 2005 to 2018. In this sample, there are no NDVI values less than zero.

#### 2.3.3. Road noise

Strategic Noise Mapping of road noise data from 2012 (measured in 2010) (Department for Environment Food & Rural Affairs, 2015) and 2017 (measured in 2015–2016) (Department For Environment Food & Rural Affairs, 2019) were obtained from Defra's Noise Team (personal communication, noise@defra.gov.uk). Details on the Strategic Road Mapping methodology performed by Defra is described elsewhere (Hepworth Acoustics for the Department of Environment Food and Rural Affairs, 2013). Briefly, Defra measured road noise in decibels (dB) at 4 m (m) above local ground level on a 10m grid across 26,000 km of major roads and 65 agglomerations under the Environmental Noise Directive (rounds 2 and 3). A 3 km buffer for roads and a 1 km buffer for agglomerations were added in order to include all noise sources affecting noise levels within the calculation area, resulting in coverage of approximately 77,000 km$^2$ of England. Major roads are identified as motorways and A-roads within agglomerations, and those with more than 3 million vehicle movements per year.

The nearest annual average road noise level for evening 7–11pm ($L_{evening}$) and night time 11pm-7am ($L_{night}$) at the centroid of the home full-postcode boundary, and for daytime 7am-7pm ($L_{day}$) at the centroid of the school full-postcode boundary, were extracted for each child in QGIS from 2005 to 2018. Due to high missingness in $L_{night}$ and high correlations between $L_{evening}$ and $L_{night}$ in the sample ($r = 0.98$), only $L_{evening}$ was used to represent children's residential road noise exposure. To construct an annual series of road noise exposure at home and school, road noise data measured in 2010 was used for 2005–2012, and that measured in 2015-16 was used for 2013–2018.

In this sample, missing road noise values represent postcodes that are not located near major roads or that are below 35 dB, where Defra indicated that major road noise would not be measurable or that data collected would represent inaccurate measurements. Children with missing road noise exposure data (24.5 %) were included in the analysis with a dummy variable in order to retain the whole sample.

#### 2.3.4. Exposure levels

In order to represent both residential and school exposure to $PM_{2.5}$, greenness and road noise, an occupancy time-weighted combined exposure measure was constructed separately for each environmental factor for each year from 2005 to 2018. These exposure measures account for 17 h of exposure at home and 7 h at school across 9 months per year when state schools are in session, with the remainder of the exposure defined at home. These estimates reflect the UK government's minimum requirements for all state schools across all academic stages (Department For Education, 2023b). In our statistical models, long-term average exposure was defined as comprising the 12-year follow-up period since Reception in September 2005 and 2006 until May of each academic assessment year at EYFSP, KS1, KS2 and KS4. In order to examine the academic trajectory, trajectory exposure was estimated using the average time-weighted environmental exposures since the last academic assessment up until each academic assessment in May at KS1, KS2 and KS4. Fig. S1 in the supplemental material presents a graphical illustration of all exposure levels used in this study.

### 2.4. Other covariates

Other individual, school and area level covariates were identified in the NPD based on previous research indicating their potential to confound the association between the co-occurring environmental exposures included in this study, $PM_{2.5}$, greenness and road noise, and academic performance (Mizen et al., 2020; Milojevic et al., 2021). Research using similar environmental exposure methodology to this study demonstrated strong relationships between air pollution, greenspace and noise and area-level socioeconomic deprivation, as well as urban-rural and regional differences (Garkov et al., 2024b). The individual level characteristics collected by the school census include cohort (child started school in September 2005 or 2006), relative age in months, gender (male or female), ethnicity (major categories as recorded by the school census: White, Black, South Asian, Chinese, Mixed or other), language (English or non-English) and eligibility for Free School Meals (FSM). The school level characteristics from SLASC include the school gender (male, female or mixed); pupils with ethnic backgrounds (as recorded in SLASC) of White (%), Black (%), South Asian (%), Chinese (%) or others (%); pupils with English as an additional language (%); pupils eligible for FSM (%); ratio of teachers to pupils; ratio of teaching assistants (TA) to teachers; and institution type (Academies, Community Schools, Voluntary Schools, Foundation Schools, Technology Colleges, Special Schools, Free Schools & Studio Schools). Area level covariates from the ONS determined at residential postcodes include the Region Code, quintiles of population density of all Output Areas (OA), and deciles of the Income Deprivation Affecting Children Index (IDACI) (from the English Indices of Deprivation) – the proportion of all children aged 0 to 15 living in income deprived families – of all Lower Super Output Areas (LSOA) (Ministry Of Housing Communities & Local Government, 2019).

### 2.5. Statistical analyses

#### 2.5.1. Study population & environmental exposures

First, summary statistics and correlations among environmental exposures, academic outcomes and covariates at each academic stage were obtained to explore the relationships between variables considered in the analyses.

#### 2.5.2. Impacts on academic performance

Multilevel mixed effects linear regression models of long-term $PM_{2.5}$ exposure since the start of school up until each assessment on total standardised academic performance at ages 4–5 (EYFSP), 6–7 (KS1), 10–11 (KS2) and 15–16 (KS4) years were applied including random effects of schools nested within Local Authority Districts (LADs). Each fully-adjusted multi-environmental exposure model includes all other environmental (greenness & road noise), individual (cohort, relative age, gender, ethnicity, language & FSM eligibility), school fixed effect (school gender, ethnicity percentages, language percentages, FSM eligibility percentages, teacher-pupil ratio, TA-teacher ratio & institution type) and areal (region, population density quintiles & IDACI deciles) characteristics. A directed acyclic graph of the main association of interest and its potential confounding factors, identified based on their relationships with exposures and outcomes and previous literature, can be found in the supplementary material (Fig. S2) (del Carmen Ruiz et al., 2016; Draper et al., 2024; Trentacosta et al., 2016; Garkov et al., 2024a; Garkov et al., 2024b; Milojevic et al., 2021). Single environmental exposure models examining each environmental factor – $PM_{2.5}$, greenness or road noise – separately, but adjusted for all other potential confounding factors were explored for comparison. Multi-environmental and single environmental exposure models unadjusted for these other individual, school and areal characteristics were also examined to compare their contribution to the models.

The multilevel mixed effects statistical models determine the contribution of long-term environmental exposures and relevant covariates to standardised academic performance scores throughout school, and allow for clustering of outcomes at school and LAD levels. In the analyses, evidence of a potential association is considered with a $p$-value $<0.05$ and little to no evidence of an association with a $p$-value $>0.05$. All results of $PM_{2.5}$, greenness and road noise exposures are expressed as the change in standardised scores for an interquartile range (IQR) increase in each average environmental measure. Analyses were performed in Stata version 17 (example Stata code provided in Supplementary Material Fig. S3).

#### 2.5.3. Impacts on academic trajectory

A further analysis was conducted to investigate children's academic trajectory at ages 6–7 (KS1), 10–11 (KS2) and 15–16 (KS4) years by employing average time-weighted exposures since the last academic measurement while accounting for the standardised score at the previous academic stage; all other aspects of the multilevel mixed effects linear regression models, including the confounder adjustment strategy, otherwise remain the same. Controlling for prior academic performance in the trajectory models allows for further consideration of unobservable characteristics in the relationships between exposures and outcomes. The sample size at ages 6–7 (KS1) years was reduced due to controlling for academic performance at ages 4–5 years (EYFSP) that was only collected for 60 % of all pupils (10 % of the first cohort; 100 % of the second cohort).

#### 2.5.4. Sensitivity analyses

Several sensitivity analyses were performed using models identical to those in the main analyses except for: 1) examining environmental exposures from one year prior to each academic measurement (1-year lag); 2) restricting the analyses to pupils with available road noise data that reside or attend schools near major roads ($n$ = 791,366); 3) excluding school characteristic covariates in order to determine their contribution to the environmental exposure-academic performance relationship; 4) restricting analyses to pupils with complete data across all Key Stages ($n$ = 315,358). In addition, the main fully-adjusted multi-environmental exposure models were stratified by the Rural Urban Classification (2011 Census) and Region Codes to examine any potential effect modifications (Department For Environment Food & Rural Affairs, 2011). Furthermore, non-linearity of the main effects of each environmental factor were explored by adding cubic polynomial terms to the main fully-adjusted multi-environmental exposure models.

## 3. Results

### 3.1. Study population & environmental exposures

After successful data linkage between environmental exposures, academic outcomes and other covariates, 553,282 children were analysed at ages 4–5 years (EYFSP), 979,978 at 6–7 years (KS1), 745,123 at 10–11 years (KS2) and 708,273 at 15–16 years (KS4) using long-term environmental exposure data. All individual, school and areal characteristics of the analytic samples from long-term multi-environmental exposure models are reported in Table 1. The majority of children are of white ethnicity (80.3 % at KS1), speak English as a first language (86.9 % at KS1) and are not eligible for free school meals (82.9 % at KS1). The most common types of schools in the sample are mixed gender (99.9 % at KS1) and community schools (67 % at KS1). Individual, school and areal characteristics of the analytic samples are largely consistent across KSs.

Children ages 6–7 years (KS1) in this sample were exposed to on average 11.04 $\mu g/m^3$ of $PM_{2.5}$, greenness levels of 0.5 (NDVI) and 44.42 dB of road noise in the long-term multi-environmental exposure model (Table 2). A sample correlational matrix among exposure estimates at ages 6–7 years (KS1) is provided in the supplementary material (Table S1). Long-term environmental exposure measures are highly correlated ($r > 0.94$ at KS1) with one-year lag and trajectory exposures. Greenness is moderately negatively correlated with $PM_{2.5}$ ($r < -0.52$ at KS1), and road noise is weakly positively correlated with $PM_{2.5}$ ($r > 0.24$ at KS1) and weakly negatively correlated with greenness ($r < -0.27$ at KS1). Exposure levels and relationships among exposures at other KSs in this sample generally reflect those at ages 6–7 years (KS1). A summary of the relationships between $PM_{2.5}$, greenness (NDVI), road noise and all individual, school and areal characteristics can also be found in the supplementary material (Table S2).

### 3.2. Impacts on academic performance

Figs. 1–3 present the estimated differences in Z-scores for an IQR increase in long-term $PM_{2.5}$ (Fig. 1), greenness (Fig. 2) and road noise (Fig. 3) at each KS in single and multi-environmental exposure models unadjusted and fully-adjusted for all other individual, school and areal characteristics, as well as in trajectory models. All fully-adjusted single and multi-environmental exposure coefficients across KSs can be found in the supplementary material (Table S3).

**Table 1**
Individual, school and area level characteristics of the analytic sample of NPD children at EYFSP (4–5 years), KS1 (6–7 years), KS2 (10–11 years) and KS4 (15–16 years) linked to long-term environmental exposures.

| | | EYFSP 4–5 years (n = 553,282) | KS1 6–7 years (n = 979,978) | KS2 10–11 years (n = 745,123) | KS4 15–16 years (n = 708,273) |
|---|---|---|---|---|---|
| Individual-level | | | | | |
| Relative age, months | Median (IQR) | 6 (6) | 6 (6) | 6 (6) | 6 (6) |
| Gender, n (%) | Male | 283,591 (51.3) | 501,485 (52.3) | 376,709 (50.6) | 355,986 (50.3) |
| | Female | 269,691 (48.7) | 478,493 (48.8) | 368,414 (49.4) | 352,287 (49.7) |
| Ethnicity, n (%) | White | 440,177 (79.6) | 786,984 (80.3) | 581,557 (78.1) | 566,639 (80) |
| | South Asian | 52,962 (9.6) | 90,453 (9.2) | 78,178 (10.5) | 67,711 (9.6) |
| | Black | 25,870 (4.7) | 44,169 (4.51) | 37,566 (5) | 32,215 (4.6) |
| | Chinese | 1649 (0.3) | 2895 (0.3) | 2350 (0.3) | 2107 (0.3) |
| | Mixed | 26,105 (4.7) | 44,891 (4.6) | 36,641 (4.9) | 31,886 (4.5) |
| | Other | 6519 (1.2) | 10,586 (1.1) | 8831 (1.2) | 7715 (1.1) |
| Language, n (%) | English | 475,064 (85.9) | 851,080 (86.9) | 634,681 (85.2) | 612,887 (86.5) |
| | Non-English | 78,218 (14.1) | 128,898 (13.2) | 110,442 (14.8) | 95,386 (13.5) |
| FSM eligible, n (%) | No | 467,545 (84.5) | 812,605 (82.9) | 611,230 (82) | 623,994 (80.1) |
| | Yes | 85,737 (15.5) | 167,373 (17.1) | 133,893 (18) | 84,279 (11.9) |
| School-level | | | | | |
| Gender, n (%) | Boys only | 52 (<0.1) | 129 (<0.1) | 327 (<0.1) | 29,924 (4.2) |
| | Girls only | 128 (<0.1) | 192 (<0.1) | 332 (<0.1) | 44,213 (6.2) |
| | Mixed | 553,102 (>99.9) | 979,657 (>99.9) | 744,464 (>99.9) | 634,136 (89.5) |
| Ethnicity %, Median (IQR) | White | 68.3 (28.9) | 67.8 (29) | 70 (29.9) | 88 (26.9) |
| | Black | 0.5 (2.5) | 0.5 (2.6) | <0.1 (3.8) | 1.2 (4.8) |
| | South Asian | 0.8 (3.7) | 0.9 (3.9) | 1.2 (5.8) | 1.9 (7) |
| | Chinese | <0.1 (0.4) | <0.1 (0.4) | <0.1 (<0.1) | 0.2 (0.4) |
| | Other | 2.4 (3.8) | 2.6 (4) | 3.2 (5.6) | 4.6 (5.4) |
| Non-English language % | Median (IQR) | 3.4 (13.6) | 3.9 (14.5) | 6.8 (20.9) | 6.5 (15.2) |
| FSM eligible pupils % | Median (IQR) | 10.4 (18.2) | 10.3 (17.5) | 13.9 (18.2) | 9.8 (10.5) |
| Teacher-pupil ratio | Median (IQR) | 22.4 (3.9) | 22.1 (4) | 21 (3.9) | 15.9 (2.3) |
| TA-teacher ratio | Median (IQR) | 0.6 (0.4) | 0.7 (0.5) | 0.6 (0.4) | 0.2 (0.1) |
| Institution type, n (%) | Academy | 119 (<0.1) | 749 (<0.1) | 28,042 (3.8) | 462,299 (65.3) |
| | Community | 374,537 (67.7) | 656,818 (67) | 450,898 (60.5) | 111,589 (15.8) |
| | Voluntary | 163,183 (29.5) | 291,385 (29.7) | 217,882 (29.2) | 67,355 (9.5) |
| | Foundation | 13,241 (2.4) | 25,932 (2.7) | 47,398 (6.4) | 55,038 (7.8) |
| | Special | 2202 (0.4) | 5094 (0.5) | 804 (0.1) | |
| | Free School | | | 99 (<0.1) | 4176 (0.6) |
| | Tech College | | | | 6245 (0.9) |
| | Studio | | | | 1571 (0.2) |
| Area-level | | | | | |
| Region, n (%) | North East | 27,138 (4.9) | 49,211 (5) | 32,834 (4.4) | 34,328 (4.9) |
| | North West | 76,605 (13.9) | 137,998 (14.1) | 101,969 (13.7) | 105,755 (14.9) |
| | Yorkshire & the Humber | 55,573 (10) | 99,285 (10.1) | 73,416 (9.9) | 68,554 (9.7) |
| | East Midlands | 49,059 (8.9) | 85,509 (8.7) | 61,043 (8.2) | 60,038 (8.5) |
| | West Midlands | 62,735 (11.3) | 111,792 (11.4) | 85,637 (11.5) | 77,783 (11) |
| | East of England | 59,855 (10.8) | 106,551 (10.9) | 81,268 (10.9) | 78,652 (11.1) |
| | London | 84,236 (15.2) | 143,214 (14.6) | 121,138 (16.3) | 100,495 (14.2) |
| | South East | 86,227 (15.6) | 153,270 (15.6) | 122,030 (16.4) | 114,778 (16.2) |
| | South West | 51,854 (9.4) | 93,148 (9.5) | 65,788 (8.8) | 67,890 (9.6) |
| Population density quintiles, n (%) | 1 (Lowest) | 107,940 (19.5) | 195,267 (19.9) | 127,553 (17.1) | 151,241 (21.4) |
| | 2 | 108,138 (19.5) | 194,642 (19.9) | 148,477 (19.9) | 147,416 (20.8) |
| | 3 | 108,928 (19.7) | 194,938 (19.9) | 154,445 (20.7) | 143,930 (20.3) |
| | 4 | 110,915 (20.1) | 196,452 (20.1) | 155,490 (20.9) | 137,079 (19.4) |
| | 5 (Highest) | 117,361 (21.2) | 198,679 (20.3) | 159,158 (21.4) | 128,607 (18.2) |
| IDACI deciles, n (%) | 1 (Most deprived) | 59,487 (10.8) | 101,353 (10.3) | 69,634 (9.4) | 55,449 (7.8) |
| | 2 | 57,016 (10.3) | 98,660 (10.1) | 73,824 (9.9) | 63,272 (8.9) |
| | 3 | 56,016 (10) | 98,013 (10) | 76,647 (10.3) | 67,095 (9.5) |
| | 4 | 55,218(10.1) | 97,396 (9.9) | 78,096 (10.5) | 70,630 (10) |
| | 5 | 54,223 (9.8) | 95,824 (9.8) | 76,550 (10.3) | 72,733 (10.3) |
| | 6 | 54,968 (9.9) | 99,067 (10.1) | 74,701 (10) | 72,774 (10.3) |
| | 7 | 54,791 (9.9) | 98,517 (10.1) | 73,470 (9.8) | 74,986 (10.6) |
| | 8 | 54,840 (9.9) | 98,649 (10.1) | 72,974 (9.9) | 74,863 (10.6) |
| | 9 | 54,332 (9.8) | 98,163 (10) | 71,688 (9.6) | 76,041 (10.7) |
| | 10 (Least deprived) | 52,391 (9.5) | 94,336 (9.6) | 77,539 (10.4) | 80,430 (11.4) |

EYFSP, Early Years Foundation Stage Profile; KS, Key Stage; N, unweighted number; IQR, interquartile range; %, weighted percentage; FSM, free school meals; TA, teaching assistants; IDACI, Income Deprivation Affecting Children Index. Population density quintile 1 (2–964), 2 (945–2852), 3 (2835–4604), 4 (4584–6751) & 5 (6699–102692). IDACI decile 1 (1–2456), 2 (2449–5131), 3 (5126–8120), 4 (8079–11362), 5 (11273–14750), 6 (14652–18273), 7 (18187–21847), 8 (21785–25407), 9 (25386–28963) & 10 (28958–32844).

Broadly, the effect sizes of long-term $PM_{2.5}$, greenness and road noise decrease with each stepped adjustment for other environmental, individual, school and areal characteristics. Specifically, there is a noticeable decrease in effect sizes for $PM_{2.5}$ (Fig. 1) with adjustment for the other environmental factors in this study (multi-environmental exposure models), whereas greenness effect sizes (Fig. 2) decrease most substantially after adjustment for individual, school and areal characteristics (fully-adjusted models). There is less variability among coefficients for road noise (Fig. 3) across models.

For $PM_{2.5}$, there is little evidence of an association with academic

**Table 2**
Summary of long-term, one-year lag and trajectory average $PM_{2.5}$, greenness and road noise exposures of the study sample.

| | | EYFSP 4–5 years | KS1 6–7 years | KS2 10–11 years | KS4 15–16 years |
|---|---|---|---|---|---|
| Number of children | Long-term | 553,282 | 979,978 | 745,123 | 708,273 |
| | 1-year lag | 553,283 | 994,211 | 772,811 | 830,137 |
| | Trajectory | | 988,045 | 760,326 | 754,120 |
| $PM_{2.5}$, μg/m$^3$ [a] | Long-term | 11.16 (3.4) | 11.04 (2.56) | 11.36 (2.23) | 10.83 (2.07) |
| | 1-year lag | 11.93 (2.7) | 10.66 (2.67) | 11.53 (2.29) | 9.82 (2.58) |
| | Trajectory | | 10.87 (2.52) | 11.48 (2.09) | 10.32 (1.93) |
| Greenness, NDVI [a] | Long-term | 0.5 (0.11) | 0.5 (0.1) | 0.49 (0.1) | 0.51 (0.09) |
| | 1-year lag | 0.5 (0.11) | 0.5 (0.1) | 0.51 (0.11) | 0.54 (0.1) |
| | Trajectory | | 0.5 (0.1) | 0.49 (0.1) | 0.52 (0.1) |
| Road noise, dB [a] | Long-term | 43.83 (7.06) | 44.22 (6.81) | 44.48 (6.49) | 44.78 (6.34) |
| | 1-year lag | 43.84 (7.27) | 44.22 (6.96) | 44.19 (6.87) | 44.42 (6.95) |
| | Trajectory | | 44.32 (6.79) | 44.44 (6.7) | 44.7 (6.63) |

[a] Median (IQR); EYFSP, Early Years Foundation Stage Profile; KS, Key Stage.

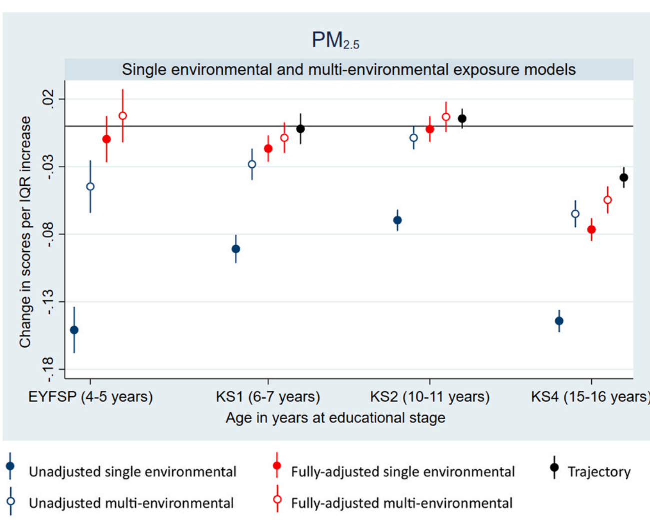


**Fig. 1.** Point estimates and 95 % confidence intervals (CI) of the estimated difference in standardised scores from multi-level mixed-effects regression models at Early Years Foundation Stage Profile (4–5 years, n = 553,282), Key Stage 1 (6–7 years, n = 979,978), Key Stage 2 (10–11 years, n = 745,123) and Key Stage 4 (15–16 years, n = 708,273) per interquartile range (IQR) increase in long-term $PM_{2.5}$ exposure (IQR for EYFSP 2.79, KS1 2.56, KS2 2.21 and KS4 2.08 in μg/m$^3$) and trajectory $PM_{2.5}$ exposure (IQR for KS1 2.53, KS2 2.06 and KS4 1.95 in μg/m$^3$). Corresponding Table S5 & Excel Table S1 (supplementary material).

performance at ages 4–5 years (EYFSP), 6–7 years (KS1) or 10–11 years (KS2) in fully-adjusted long-term multi-environmental exposure models. At ages 15–16 years (KS4), an adverse relationship is observed between long-term $PM_{2.5}$ and academic performance in the fully-adjusted multi-environmental exposure model, such that an IQR (2.08 μg/m$^3$) increase in ambient $PM_{2.5}$ exposure is associated with −0.055 (95 % CI: 0.064, −0.045) lower Z-scores (Fig. 1).

Greater exposure to long-term greenness shows no appreciable association with academic performance at ages 4–5 years (EYFSP) in the fully-adjusted multi-environmental exposure model. However, a change from the lowest to the highest quartile of greenness exposure (0.1 in

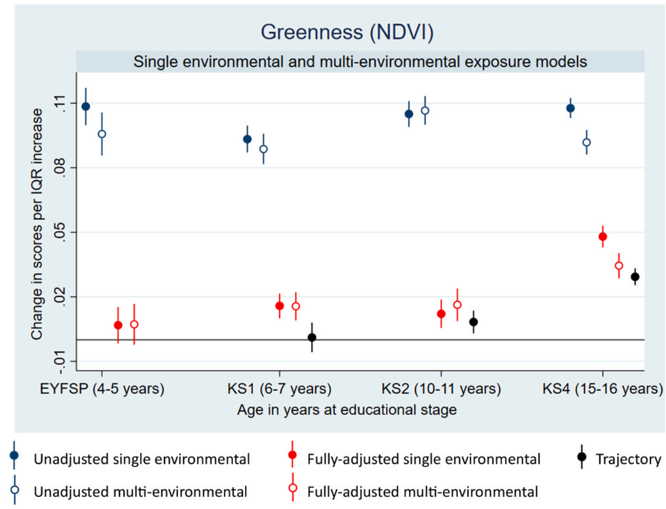


**Fig. 2.** Point estimates and 95 % confidence intervals (CI) of the estimated difference in standardised scores from multi-level mixed-effects regression models at Early Years Foundation Stage Profile (4–5 years, n = 553,282), Key Stage 1 (6–7 years, n = 979,978), Key Stage 2 (10–11 years, n = 745,123) and Key Stage 4 (15–16 years, n = 708,273) per interquartile range (IQR) increase in long-term greenness exposure (IQR for EYFSP 0.11, KS1 0.10, KS2 0.10 and KS4 0.10 in NDVI) and trajectory greenness exposure (IQR for KS1 0.10, KS2 0.10 and KS4 0.10 in NDVI). Corresponding Table S5 & Excel Table S2 (supplementary material).

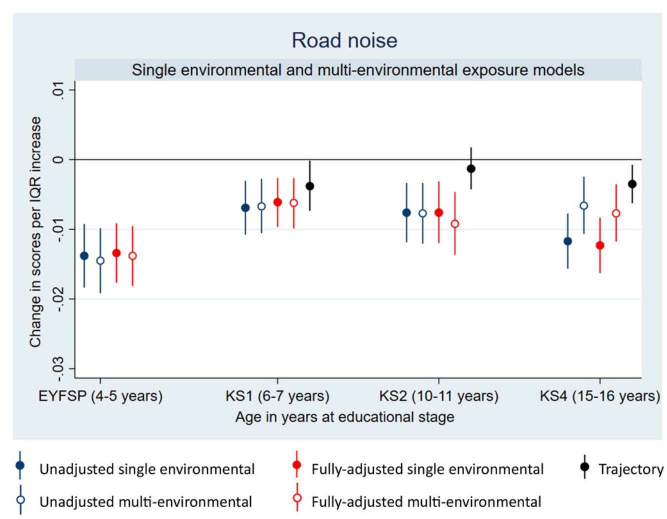


**Fig. 3.** Point estimates and 95 % confidence intervals (CI) of the estimated difference in standardised scores from multi-level mixed-effects regression models at Early Years Foundation Stage Profile (4–5 years, n = 553,282), Key Stage 1 (6–7 years, n = 979,978), Key Stage 2 (10–11 years, n = 745,123) and Key Stage 4 (15–16 years, n = 708,273) per interquartile range (IQR) increase in long-term road noise exposure (IQR for EYFSP 7.06, KS1 6.81, KS2 6.56 and KS4 6.32 in dB) and trajectory road noise exposure (IQR for KS1 IQR 6.8, KS2 IQR 6.7 and KS4 IQR 6.61 in dB). Corresponding Table S5 & Excel Table S3 (supplementary material).

NDVI) indicates 0.016 (95 % CI: 0.009, 0.022), 0.016 (95 % CI: 0.009, 0.024) and 0.035 (95 % CI: 0.029, 0.04) higher Z-scores at ages 6–7 years (KS1), 10–11 years (KS2) and 15–16 years (KS4), respectively, in fully-adjusted multi-environmental exposure models (Fig. 2).

There are observable −0.014 (95 % CI: 0.018, −0.01), −0.006 (95 % CI: 0.01, −0.003), −0.009 (95 % CI: 0.014, −0.005) and −0.008 (95 % CI: 0.012, −0.004) lower Z-scores at ages 4–5 years (EYFSP), 6–7 years (KS1), 10–11 years (KS2) and 15–16 years (KS4), respectively, related to each IQR (EYFSP 7.06, KS1 6.81, KS2 6.56 and KS4 6.32 in dB) increase in long-term road noise exposure (Fig. 3) in fully-adjusted multi-environmental exposure models.

### 3.3. Impacts on academic trajectory

Figs. 1–3 also show the results of the trajectory models that account for academic performance at the previous KS when examining the associations between $PM_{2.5}$ (Fig. 1), greenness (Fig. 2) and road noise (Fig. 3) and standardised scores. The trajectory models demonstrate attenuated relationships across KSs between environmental exposures and academic performance compared to fully-adjusted long-term multi-environmental exposure models. Furthermore, there is no longer any evidence of an association between greenness exposure at ages 6–7 years (KS1), or road noise at ages 10–11 years (KS2), and academic performance in the trajectory models.

An IQR (1.95 μg/m$^3$) increase in trajectory $PM_{2.5}$ exposure is related to −0.038 (95 % CI: 0.045, −0.031) lower Z-scores at ages 15–16 years (KS4), accounting for academic performance at ages 10–11 years (KS2), in the fully-adjusted trajectory exposure model (Fig. 1).

IQR (0.1 NDVI) increases in trajectory greenness exposure are related to 0.008 (95 % CI: 0.003, 0.013) and 0.029 (95 % CI: 0.026, 0.033) higher Z-scores at ages 10–11 (KS2) and 15–16 (KS4) years, respectively, after accounting for prior academic performance, in fully-adjusted trajectory exposure models (Fig. 2).

IQR (KS1 6.8 & KS4 6.61 in dB) increases in trajectory road noise exposure are associated with −0.004 (95 % CI: 0.007, −0.001) and −0.004 (95 % CI: 0.006, −0.001) lower Z-scores at ages 6–7 (KS1) and 15–16 (KS4) years, respectively, after considering prior academic performance, in fully-adjusted trajectory exposure models (Fig. 3).

### 3.4. Sensitivity analyses

The sensitivity analyses examining the relationships with 1-year lag exposure, restricted road noise, without school characteristics and restricted to pupils with complete data produce results that largely confirm the findings from the main models (Supplementary Material Figs. S4–6). Stratification by urban-rural and regions suggests the effects $PM_{2.5}$ (at KS4) and greenness (at KS1, KS2 & KS4) on academic performance may be more pronounced in rural areas, and those of road noise (at KS2 & KS4) in London, but the results are generally in keeping with findings from the main models (Supplementary Material Figs. S7–12). Furthermore, significant non-linearity was observed between environmental cubic polynomial terms and predicted academic scores in seven of the twelve environment-outcome associations studied. However, the linear associations presented in the main results reasonably approximate the polynomial curves across the majority of the exposure range in the sample (Supplementary Material Fig. S13).

All numerical data from the main and sensitivity analyses can be found in the supplementary material Excel Tables S1–12.

## 4. Discussion

This large-scale national study of children attending state schools in England demonstrates some associations between long-term exposure to $PM_{2.5}$, greenness and road noise and academic performance throughout school. There were no appreciable associations until the final year of exams at 15–16 years (KS4) for $PM_{2.5}$, where a negative relationship was observed between greater exposure and standardised scores. For greenness, beneficial associations between greater exposure and academic performance were noted throughout school except at the initial measurement at 4–5 years (EYFSP). Road noise demonstrated small yet measurable negative relationships with academic performance in every age group. For each interquartile range (IQR) increase in long-term environmental exposures at 15–16 years (KS4), $PM_{2.5}$ demonstrated the greatest association with −5 % lower standardised scores, followed by greenness with 3 % higher scores, and road noise with −1 % lower scores in fully-adjusted multi-exposure models. These results are comparable in magnitude to other research findings for $PM_{2.5}$ (Milojevic et al., 2021), greenness (Wing et al., 2019) and road noise (Tangermann et al., 2023).

In the sensitivity analyses, the associations between environmental factors and academic performance were substantially greater in single exposure and unadjusted models, emphasising the importance of accounting for related environmental, individual, school and areal factors. Prior academic performance may also be a key confounding factor, as relationships were noticeably attenuated in the trajectory model. Analyses by urban-rural indicate that the relationships of $PM_{2.5}$ and greenness with academic performance may be stronger in rural areas, contrary to expected patterns as generally $PM_{2.5}$ is higher in urban areas (Montes-González et al., 2018) and greenness shows greater protective effects among urban populations (Marmot et al., 2020). In stratified analyses, the relationship between road noise and academic performance is also more pronounced in London compared to other regions, which may reflect a greater number of major roads allowing for more precision in the estimate. Finally, the non-linear associations demonstrate complexity akin to other research (Klatte et al., 2016; Claesen et al., 2021), however the dominant trend across the majority of the sample supports linear interpretation.

The results are in keeping with some prior research of $PM_{2.5}$ and academic performance. A recent national study of Danish 16-year-olds found −0.99 decreases in school grade point average related to 5 μg/m$^3$ increases in life-time residential $PM_{2.5}$ exposure using a comparable statistical model (Lim et al., 2024). Other US studies using administrative data produce smaller effect sizes below −0.01 for performance in reading and mathematics among 8-14-year-olds per IQR increase in cross-sectional $PM_{2.5}$ exposure at school (Lam et al., 2023; Lu et al., 2021). In contrast, a Welsh study of the National Pupil Database did not detect any relationships between residential and school $PM_{2.5}$ and academic performance at 15–16 years (Mizen et al., 2020). Generally, research in the area is cross-sectional (Clark-Reyna et al., 2016; Mullen et al., 2020), based solely on residential or school exposure (Lertxundi et al., 2019; Requia et al., 2022), with smaller sample sizes (Alvarez-Pedrerol et al., 2017; Gui et al., 2020), without accounting for other environmental and school characteristics (Balakrishnan and Tsaneva, 2021; Chiu et al., 2016), or examines associations exclusively in younger age groups (Grineski et al., 2020; Balalian et al., 2022).

Compared to $PM_{2.5}$, most studies of greenspace and academic performance focus on later childhood and adolescence (Kweon et al., 2017; Requia and Adams, 2022), and are conducted at the school-level without consideration of individual-level characteristics or prior academic performance (Tallis et al., 2018; Sivarajah et al., 2018; Li et al., 2019). However, a large-scale longitudinal study of 8-16-year-olds in US public schools found that school greenness (NDVI) was related to similar positive increments in composite English and mathematics performance to those in this study (Wing et al., 2019). Other long-term research in early childhood is limited or has not identified direct associations between greenness and academic performance (Ahmed et al., 2022; Markevych et al., 2019; Singh et al., 2023; Fernandes et al., 2023). Nevertheless, these studies may lack the longitudinal design and large sample needed to identify an association due to a long-term exposure mechanism (Beere and Kingham, 2017; Browning and Locke, 2020; de Keijzer et al., 2016).

Previous evidence of ambient noise and academic performance focuses on exposures and outcomes in middle childhood across a range of noise sources (Seabi et al., 2015; Matheson et al., 2010), and includes a relatively limited set of confounding factors, such as age, gender and socio-economic indicators (Papanikolaou et al., 2015). Multi-national studies also suggest that although residential and school noise exposures may be highly correlated, they do not both consistently relate to academic or cognitive performance (Clark et al., 2006; Pujol et al., 2013; Tangermann et al., 2023). Other research using the NPD did not find any notable relationships between road noise around schools and pupils' achievement at ages 10–11 (KS2) or 15–16 (KS4) years in London (Xie et al., 2011). The mixed results may reflect inconsistencies in the type and pathway of noise exposure, insufficient power, or overlook the associated environmental exposures (Thompson et al., 2022; Hahad et al., 2022).

Multi-exposure studies indicate some evidence of independent detrimental effects of $NO_2$, $PM_{2.5}$ and ambient noise, and beneficial associations with greenness across age groups (Julvez et al., 2021; Foraster et al., 2022; van Wel et al., 2021; Minaravesh and Aydin, 2023). This paper builds on the evidence by including both residential and school measurements throughout development. Although cross-sectional studies provide an accurate snapshot of exposure, they may not capture the long-term influence of the environment on cognition (Minaravesh and Aydin, 2023). Furthermore, this study attempts to fully reflect the myriad of factors affecting children's academic performance alongside environmental factors (del Carmen Ruiz et al., 2016). Nevertheless, other multi-exposure studies using mediation analyses may provide stronger causal evidence of the pathway from environment to cognition (Claesen et al., 2021; Binter et al., 2022; Carver et al., 2022; Asta et al., 2021).

Although the trajectory analysis allows for increased control for unobserved effects (Minaravesh and Aydin, 2023), the attenuated results in this model, particularly for greenness and road noise, suggest that some correlated factors may be unmeasured (Haines et al., 2002). As individual-level socioeconomic status was only measured through children's free school meal eligibility, it is possible that residual confounding may also affect this result, especially in the later school years. Furthermore, road noise was only measured twice over the study period along major roads; thus, it may be susceptible to exposure misclassification due to unmeasured noise among children based further from roads (Matheson et al., 2010). Greenness exposure assessments may also have been improved by using a buffer (Wing et al., 2019), however this methodology was not feasible within this dataset. In addition, the lack of associations between $PM_{2.5}$ and academic performance at earlier ages may be due to the absence of exposure measurements prior to the start of formal schooling (Milojevic et al., 2021). Finally, the outcome variable differs by age group, challenging comparability over time, however this is common for academic assessments (Browning and Rigolon, 2019; Castagna et al., 2022; Thompson et al., 2022). Thus, the challenges described are common in the research area, and the methodology utilises the best available data to produce results that are strongly placed among other recent multi-exposure studies (Thompson et al., 2024; Saenen et al., 2023).

The limitations of this study may inform future research directions. Higher resolution or direct exposure assessments since birth instead of modelled data could improve the accuracy of children's exposure classification (van Kempen et al., 2012). Given that environmental exposures and academic outcomes are strongly related to socio-economic indicators (Julvez et al., 2021), future research may also benefit from including measures that encompass the socio-economic spectrum, in addition to more family-level factors (van Wel et al., 2021). Finally, academic performance remains a proxy indicator of cognition (Requia and Adams, 2022); further large-scale multi-exposure studies that examine cognitive ability longitudinally may generate insight into the environment-cognition link (Milojevic et al., 2021). The results of this study are in contrast to the null findings of the authors' previous paper (Garkov et al., 2024a), which may reflect the greater power of this study, distinct outcomes, sample selection or insufficient adjustment for key individual and family level factors. Further investigation is needed to identify the source of this discrepancy.

Given the comprehensive administrative data used in this study, the findings provide a fairly precise representation of the relationships between $PM_{2.5}$, greenness and road noise exposure and academic performance in England. Despite modest effect sizes, the large-scale dataset and other results of a similar magnitude suggest relevant implications for future education, economic and work outcomes related to academic performance at the national level, particularly at the end of school (Mizen et al., 2020). Therefore, the strongest evidence among the research findings is for adverse $PM_{2.5}$ and road noise and beneficial greenness associations with academic performance among adolescents in their final year of school in England, even when considering prior achievement. In conclusion, this study demonstrates evidence in support of action to reduce exposure to $PM_{2.5}$ and road noise, and improve exposure to greenness in residential and school areas to prevent harm and improve health.

## CRediT authorship contribution statement

**Sophia Garkov:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lorraine Dearden:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Conceptualization. **Ben Armstrong:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Formal analysis, Conceptualization. **Ai Milojevic:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Funding acquisition, Formal analysis, Conceptualization.

## Ethics

Ethics approval was obtained from the London School of Hygiene & Tropical Medicine Ethics Committee, reference #26559. Data sharing approval for this project was provided by the Department for Education (DfE) and all data linkage and analyses were performed in the Office for National Statistics (ONS) Secure Research Service (SRS) following its data protection guidelines and privacy rights of human subjects.

## Data statement

The data described in this paper is not suitable for sharing publicly due to data sensitivity, as the data includes personally identifiable information. Requests to access the National Pupil Database should be made to the Department for Education (DfE). This work was undertaken in the Office for National Statistics (ONS) Secure Research Service (SRS) using data from ONS and other owners and does not imply the endorsement of the ONS or other data owners.


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## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sophia Garkov reports a relationship with UK Health Security Agency that includes: employment. Ai Milojevic reports a relationship with UK Health Security Agency that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2025.127034.

## Data availability

The data that has been used is confidential.

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